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Halodoc Adoption Model: Integration of UTAUT2, Perceived Risk, and Trust with PLS-SEM

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ABSTRACT

The development of digital health technology, also known as healthtech, has transformed the opportunities and ways people access healthcare, particularly through telemedicine. In Indonesia, Halodoc has become one of the most widely used telemedicine platforms, offering easy access and affordable online healthcare services. Despite its various conveniences, user adoption remains inconsistent due to persistent issues and public perceptions regarding perceived risk and lack of trust in online consultation methods. This study aims to develop a model for Halodoc adoption by developing the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) with perceived risk and trust in medical personnel. Using a quantitative approach, data responses were collected from online Halodoc users through purposive sampling and analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) techniques with the help of SmartPLS. The results show that only facilitating conditions, habit, and price value have a significant influence on behavioral intention to adopt Halodoc. Extensive factors suspected of influencing Halodoc adoption, namely perceived risk and trust in medical personnel, did not have a significant influence, especially in the Indonesian context. The results of this study add to the role and benefits of UTAUT2 in the healthcare context, especially in Indonesia, with managerial implications for enhancing the role of facilitating conditions, habits, and price value in order to increase the adoption of Halodoc and other digital healthcare in Indonesia.

***Keywords**: Perceived risk, PLS-SEM, telemedicine, trust, UTAUT2*

1. INTRODUCTION

The era of digital transformation has shaped healthcare utilization through online consultations and remote monitoring, enabling patients to access medical services efficiently (Dwivedi et al., 2019). The COVID-19 pandemic has accelerated this shift in healthcare mechanisms, making telemedicine a crucial medium for conducting health consultations during lockdowns (Yan et al., 2021). In Indonesia, telemedicine platforms such as Halodoc, Alodokter, and KlikDokter have rapidly expanded, offering virtual and online consultations and medication delivery (Lu et al., 2023). Even after the pandemic ended, users continued to rely on digital platforms for healthcare services, demonstrating a shift in healthcare-seeking behavior (Zhan et al., 2024).

Despite its widespread availability and access, telemedicine adoption rates remain inconsistent, particularly in Indonesia. Many users remain reluctant or even refuse to rely entirely on online medical consultation services due to concerns about privacy, diagnostic reliability, and trust in medical personnel (Hawa et al., 2023; Meylani et al., 2021). Previous research has concluded that this user rejection behavior is influenced by user perceptions of technological usefulness, ease of use, and risk (Hayat et al., 2024; Kurnia, 2021). Therefore, research into telemedicine adoption using a robust theoretical framework, such as the Unified Theory of Acceptance and Use of Technology 2, is feasible and important.

The UTAUT2 model, developed by Venkatesh et al. (2022), uses seven factors for technology adoption: performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, and habit. This construct has been validated in various contexts and studies, such as e-commerce, fintech, and mobile health (Octavius & Antonio, 2021; Schmitz et al., 2022). However, when applied directly to healthcare technology, UTAUT2 is still considered inadequate because health-related decisions are also thought to be influenced by psychological and emotional factors, such as trust and perceived risk (Dwivedi et al., 2019; Pappas & Woodside, 2021).

Perceived risks indicate user concerns about privacy, security, and credibility when consulting online (Hayat et al., 2024). Trust, on the other hand, is a factor that determines how confident users feel in the abilities, expertise, and professionalism of online healthcare providers (Zhan et al., 2024). Previous research has shown that user trust increases users' intention to continue using digital platforms, especially in high-risk service environments like healthcare (Chrisdianti et al., 2023). This previous research demonstrates the importance of developing UTAUT2 with other extension factors, such as these two constructs.

In Indonesia, Halodoc has been recognized as a pioneering digital health platform with strong growth and increasing user adoption. However, previous research indicates that user concerns regarding credibility, data protection, and accuracy of doctors' diagnoses are still suspected of discouraging people from using this service (Hawa et al., 2023; Meylani et al., 2021). Furthermore, research conducted by Prasetio et al. (2025) indicates that constructs such as trust and perceived reliability play a significant role in determining adoption intentions in digital platforms. Based on this, this research can contribute to enriching the role of UTAUT2 in the healthcare context.

While previous research has explored the determinants of mHealth and telemedicine adoption, there is little research that combines perceived risk and trust in medical personnel or professionals with UTAUT2 in Indonesia. Using Partial Least Squares Structural Equation Modeling (PLS-SEM), this study examines the relationship between nine constructs and behavioral intention to adopt Halodoc. The following describes the development of previous research that serves as the basis for this study.

Table 1. Past Researches Development

Author	Context	Model	Findings	Limitations
(Venkatesh et al., 2022)	General adoption of technology	UTAUT2	Identifying seven major determinants of behavioral intention (PE, EE, SI, FC, HM, PV, HT)	Does not include psychological constructs such as risk perception and trust
(Yan et al., 2021)	mHealth Application (global)	Quantitative, SEM	Performance expectations and social influence drive continued use of health apps	Focuses on continued intent, not initial adoption; does not include contextual factors
(Dwivedi et al., 2019)	Adoption of information systems	UTAUT revised	Highlighting social and cultural influences on technology adoption	Not focused on the context of healthcare services
(Schmitz et al., 2022)	Cross-border telemedicine	UTAUT2 modified	Finding country-specific variations in telemedicine adoption	Does not address emotional or belief factors
(Octavius & Antonio, 2021)	mHealth Application (Indonesia)	UTAUT2, SEM	Social influences and habits have a significant impact on adoption.	Does not include trust or risk perception factors
(Chrisdianti et al., 2023)	Health tracker app	UTAUT2, SEM	Hedonic motivation and price value increase the intention to use	Focus on personal tracking, not online consultations
(Hayat et al., 2024)	e-Health Application (developing economy)	Expanded TAM	Perceptions of privacy and risk are major barriers	Not integrated with UTAUT2 framework
(Zhan et al., 2024)	Voice AI in healthcare	Trust-based model	Trust in technology significantly influences the intention to use a health AI assistant.	Focus on AI-based systems, not telemedicine platforms
(Hawa et al., 2023)	Halodoc Users (Indonesia)	Descriptive study	Halodoc improves health literacy	Does not use a theoretical framework or behavioral analysis
(Meylani et al., 2021)	Halodoc Users (Indonesia)	Quantitative, Regression	Usefulness and reliability of information are the main predictors	Does not test structural relationships between constructs
(Prasetio et al., 2025)	Digital platform (E-commerce)	SEM	Trust and reliability drive repeat purchase intentions	Focus on consumer products, not healthcare services
(Kurnia, 2021)	Digital wallet users (Indonesia)	UTAUT2 Extension	Social and cultural connectedness influences usage intentions	Limited to the fintech context
(Lu et al., 2023)	Telemedicine (Indonesia)	TAM, SEM	The pandemic has increased the adoption of telemedicine	Limited to the context of COVID-19
(Pappas & Woodside, 2021)	Information Systems dan pemasaran	fsQCA	Demonstrates multifactorial interactions in adoption behavior	Focusing on qualitative combinations, not PLS-SEM

Table 1 this study aims to identify factors that influence user behavioral intention towards adopting UTAUT2-based Halodoc services, examine the influence of perceived risk and trust in medical personnel on behavioral intention, and provide strategic recommendations for telemedicine providers to increase the adoption of this service. By developing the UTAUT2 model along with extension factors, this study contributes both theoretically and practically. Theoretically, this study expands the application of UTAUT2 in the health or healthcare context. Meanwhile, in practice, this study provides practical and strategic insights for Halodoc and other telemedicine service providers to improve the quality and service in digital health adoption, especially in Indonesia.

2. FOCUS AND SCOPE

The scope of this research focuses on analyzing the factors influencing users' behavioral intentions to adopt the Halodoc telemedicine service, based on a UTAUT2 model developed with extension variables of perceived risk and trust in medical personnel. The research problem involves understanding the extent to which constructs such as facilitating conditions, habit, price value, and other UTAUT2 variables contribute to users' intentions to use Halodoc. This study also investigates whether perceived risk and trust in medical personnel play a role in explaining the intention to adopt digital health technology in Indonesia.

The study was conducted with several limitations to maintain its focus. These limitations include selecting only the Halodoc app, using a purposive sampling technique that requires respondents to have used Halodoc at least once, a final sample size of 100 respondents, and the predominance of respondents from the 18–25 age group (Gen Z). Furthermore, the study employed only a quantitative approach based on PLS-SEM, so the analysis results focus on the model's predictive ability rather than a more in-depth qualitative exploration.

With this scope, this study was designed to generate empirical insights into the factors that most influence user adoption intentions for Halodoc telemedicine, as well as highlight which variables have no significant influence in the context of a young, digitally native user group. The results are expected to provide a comprehensive overview of telemedicine adoption patterns and provide a basis for developing more relevant theoretical models and practical strategies in the future..

3. MATERIAL AND METHOD

This research was conducted using a quantitative explanatory research method aimed at examining the causal relationships between constructs influencing behavioral intention to adopt Halodoc. This research framework is based on the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) model developed by Venkatesh et al. (2022) and expanded with two extension constructs, namely perceived risk and trust in medical personnel, to more comprehensively understand the adoption of telemedicine services, particularly in Indonesia. The following is the theoretical framework for this study.

Based on the development of the UTAUT2 model with the extension factors or constructs identified in the theoretical framework, the following hypotheses are developed in this study:

1. H_1: Effort Expectancy (EE) has a significant influence on Behavioral Intention (BI)
2. H_2: Facilitating Conditions (FC) have a significant influence on Behavioral Intention (BI)
3. H_3: Hedonic Motivation (HM) has a significant influence on Behavioral Intention (BI)
4. H_4: Habit (HT) has a significant influence on Behavioral Intention (BI)
5. H_5: Performance Expectancy (PE) has a significant influence on Behavioral Intention (BI)
6. H_6: Performance Risk (PER) has a significant influence on Behavioral Intention (BI)
7. H_7: Privacy Risk (PRR) has a significant influence on Behavioral Intention (BI)
8. H_8: Psychological Risk (PSR) has a significant influence on Behavioral Intention (BI)
9. H_9: Price Value (PV) has a significant influence on Behavioral Intention (BI)
10. H_{10}: Social Influence (SI) has a significant influence on Behavioral Intention (BI)
11. H_{11}: Trust in medical personnel (TP) has a significant influence on Behavioral Intention (BI)

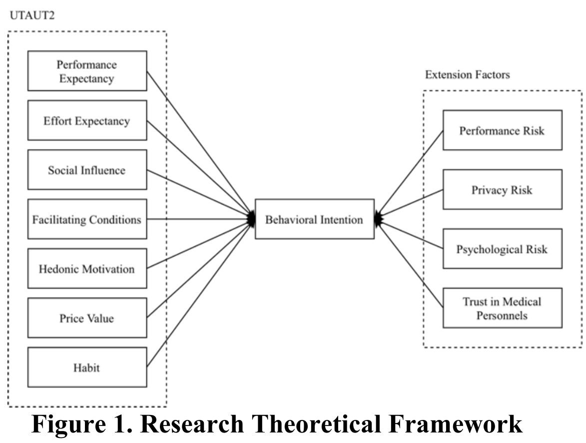

Figure 1. Research Theoretical Framework

Figure 1 this model was analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM), which is suitable for exploring models with multiple constructs and indicators (Hair et al., 2017). PLS-SEM was chosen as the processing and analysis technique in this study due to its ability to estimate complex relationships, test the reliability and validity of measurement models, and test the structural model (Ningsi & Agustina, 2018). The analysis was conducted using SmartPLS 4.0.

This study was conducted on a population of Halodoc app users in Indonesia using a purposive sampling technique. Respondents were selected based on the criteria of having owned and used the Halodoc app at least once and being over 18 years of age. The following are the factors and statement items based on the modified UTAUT2 and the extension factors in the theoretical framework developed in this study, which focuses on the Halodoc telemedicine app.

Table 2. Definition and Items of Construct

Factor	Definition	Question Items	
Performance Expectancy (PE)	How appropriate is the performance produced by the digital application on the user's smartphone in meeting the user's needs when using the Halodoc service (Venkatesh et al., 2020)	PE1	I think the application on the Halodoc service helps in achieving my goal of using this service quickly (modified from Venkatesh et al., 2020, 2022)
		PE2	In my opinion, I can comfortably use the application on the Halodoc service (modified from Venkatesh et al., 2020, 2022)
		PE3	In my opinion, the application on the Halodoc service is useful for me (modified from Venkatesh et al., 2020, 2022)
		PE4	In my opinion, using the application on the Halodoc sharing service is in accordance with my expectations (modified from Venkatesh et al., 2020, 2022)
Effort Expectancy (EE)	How much effort do users need to expend when using the Halodoc service application on a smartphone (Ratan et al., 2021; Venkatesh et al., 2022)	EE1	In my opinion, learning to use the application on the Halodoc service is easy (modified from Venkatesh et al., 2020, 2022)
		EE2	In my opinion, using the application on the Halodoc service is easy (modified from Venkatesh et al., 2020, 2022)
		EE3	In my opinion, my interaction with the application on the Halodoc service was clear and easy to understand (modified from Venkatesh et al., 2020, 2022)
Facilitating Conditions (FC)	How good are the conditions of the facilities in carrying out interactions on the Halodoc service application (Venkatesh et al., 2020)	FC1	I feel that I have the necessary resources to be able to use the Halodoc service application (modified from Venkatesh et al., 2020, 2022)
		FC2	I feel that I have the necessary knowledge to be able to use the Halodoc service application (modified from Venkatesh et

			al., 2020, 2022)
		FC3	I feel that the Halodoc service application is compatible with the smartphone I use (modified from Venkatesh et al., 2020, 2022)
		FC4	In my opinion, I can get help from other people when I have difficulty using the Halodoc service application (modified from Venkatesh et al., 2020, 2022)
Social Influence (SI)	How much does a person intend to use Halodoc services based on recommendations from people they consider important (Venkatesh et al., 2020)	SI1	People who are important to me think that I should use Halodoc services (modified from Venkatesh et al., 2022)
		SI2	People who influence me think that I should use Halodoc services (modified from Venkatesh et al., 2022)
		SI3	A person I respect suggested me to use Halodoc services (modified from Venkatesh et al., 2022)
Hedonic Motivation (HM)	How much motivation behind someone's desire to use Halodoc services is based solely on pleasure (Venkatesh et al., 2022)	HM1	In my opinion, using Halodoc services is a pleasant thing (modified from Venkatesh et al., 2022)
		HM2	In my opinion, I can enjoy using Halodoc services (modified from Venkatesh et al., 2022)
Price Value (PV)	How much does it cost to pay for Halodoc services for someone to have the intention to use them (Venkatesh et al., 2022)	PV1	In my opinion, the price for using Halodoc services is reasonable (modified from Venkatesh et al., 2022)
		PV2	In my opinion, the price for using Halodoc services is commensurate with what I get (modified from Venkatesh et al., 2022)
		PV3	I feel that the current price for using Halodoc services is the right price (modified from Venkatesh et al., 2022)
Habit (HT)	A person's habit of using Halodoc services as the first choice of existing alternatives (Venkatesh et al., 2022)	HT1	In my opinion, using Halodoc services can become a habit for me (modified from Venkatesh et al., 2022)
		HT2	In my opinion, I can get addicted to using Halodoc services (modified from Venkatesh et al., 2022)
		HT3	I feel I should use Halodoc services

			(modified from Venkatesh et al., 2022)
Behavioral Intention (BI)	A person's intention to use e-scooter sharing services continuously (Venkatesh et al., 2022)	BI1	I intend to use Halodoc services in the future (modified from Venkatesh et al., 2022)
		BI2	I will always try to use Halodoc services to meet my needs (modified from Venkatesh et al., 2022)
		BI3	I plan to use Halodoc services as often as possible (modified from Venkatesh et al., 2022)
Trust in Medical Personnel (TP)	Trust in the intention of medical personnel to act in the best interests of the patient and the competence of medical personnel in providing the necessary care (Anderson & Dedrick, 2017; Kuen et al., 2023)	TP1	Doctors usually pay attention to and prioritize my needs (modified from Anderson & Dedrick, 2017; Kuen et al., 2023)
		TP2	I trust that the doctor will put my medical needs above all other considerations when caring for me (modified from Anderson & Dedrick, 2017; Kuen et al., 2023)
		TP3	The doctor is qualified to treat the medical problem I am experiencing (modified from
			Anderson & Dedrick, 2017; Kuen et al., 2023)
Performance Risk (PER)	The extent to which a person believes that Halodoc did not go as planned and did not deliver the expected results (Grewal et al., 2021; Kuen et al., 2023)	PER 1	I am worried whether Halodoc will actually work as it should (modified from Kuen et al., 2023; Stone & Grønhaug, 2023)
		PER 2	I would be worried that Halodoc would not provide the benefits I expected (modified from Kuen et al., 2023; Stone & Grønhaug, 2023)
		PER 3	The thought of using Halodoc makes me worry about how reliable the service will be (modified from Kuen et al., 2023; Stone & Grønhaug, 2023)
Privacy Risk (PRR)	How likely is the loss of control over sensitive personal data (Featherman & Pavlou, 2020; Kuen et al., 2023)	PRR 1	In my opinion, Halodoc will collect too much user information (modified from Kuen et al., 2023; Rauschnabel et al., 2018)
		PRR 2	I am worried that my personal information will be misused when the Halodoc application is open (modified

			from Kuen et al., 2023; Rauschnabel et al., 2018)
		PRR 3	I am worried that my personal information can be accessed by unknown parties when I use Halodoc in my daily life (modified from Kuen et al., 2023; Rauschnabel et al., 2018)
Pyschological Risk (PSR)	The extent to which a person experiences psychological stress or anxiety when using Halodoc (Kuen et al., 2023; Stone & Grønhaug, 2023)	PSR1	The thought of using Halodoc makes me feel psychologically uncomfortable (modified from Kuen et al., 2023; Stone & Grønhaug, 2023)

Table 2 data was collected through an online questionnaire system and shared through social media. A total of 142 respondents were initially selected, representing data before screening. After purposive sampling, 100 respondents were selected, each of whom had used the Halodoc app. According to Hair et al. (2017), the minimum data size for PLS-SEM analysis is 10 times the number of indicators for a construct in the research model. In this study, the construct with the most indicators was privacy risk, with five indicators, requiring a minimum of 50 data sets. Therefore, the 100 respondents in this study met the requirements for PLS-SEM analysis.

The research was analyzed using the PLS-SEM method, which consists of two stages: measurement model or outer model evaluation and structural model or inner model evaluation (Hair et al., 2017). Measurement model evaluation tests construct reliability through internal consistency reliability by examining the composite reliability (CR) value for each construct. A construct is considered reliable when the CR value is above the threshold of 0.708 (Hair et al., 2017). Next, construct validity or convergent validity is tested by examining the Average Variance Extracted (AVE) value. AVE indicates the extent to which indicators within the same construct correlate with each other. If the AVE value is below 0.50, it indicates that the construct fails to meet convergent validity requirements and should be considered for elimination (Hair et al., 2017).

Furthermore, Outer Loadings are useful for testing indicator reliability, namely to determine whether each indicator adequately represents and explains its respective construct (Hair et al., 2017). Outer Loadings above 0.70 indicate that the indicator adequately represents the construct and should be retained. Conversely, indicators with Outer Loadings below 0.40 should be eliminated from the research model. Meanwhile, indicators with Outer Loadings values between 0.40 and 0.70 can be considered for elimination or retention. Elimination can be performed if it increases the CR and AVE values, or vice versa (Hair et al., 2017).

Furthermore, in the measurement model evaluation, a discriminant validity analysis is conducted to ensure each construct can be distinguished from the others (Hair et al., 2017). Discriminant validity is measured using the Fornell-Larcker Criterion, requiring the square root of the AVE of a construct to be greater than its correlation with other constructs. The next analysis in the measurement model evaluation is a multicollinearity test, which uses the variance inflation factor (VIF) value. A VIF value below 5 indicates no significant multicollinearity problem (Hair et al., 2017).

After ensuring that the constructs and indicators in the research model meet reliability and validity requirements, a structural model evaluation is conducted to measure the predictive ability of the research model and prove the hypotheses in the study (Hair et al., 2017; Sarstedt et al., 2020). In the structural model evaluation, bootstrapping was performed on 5,000 subsamples to obtain path coefficients and p-values for each hypothesis (Hair et al., 2017; Sarstedt et al., 2020). The path coefficient value can range from -1, indicating a more negative correlation, to 1, indicating a more positive correlation between the independent and dependent constructs. Meanwhile, the hypothesis is said to prove that the independent construct has a significant influence on the dependent when the p-value is below 0.05 (Hair et al., 2017; Sarstedt et al., 2020). In the research model, a coefficient of determination (R2) analysis was also carried out to show how well the construct can explain the dependent variable in the research model (Hair et al., 2016).

4. DISCUSSION

PLS-SEM was conducted using SmartPLS 4.0 to explore and prove eleven hypotheses in this research model. The results of the measurement model evaluation are shown in Table 3. Based on the results in Table X, all constructs have met the internal consistency reliability requirements with all Composite Reliability (CR) values being above 0.708. In addition, all AVE values, which indicate the convergent validity of each construct, have also met the requirements with all AVE values being above 0.50. Furthermore, the reliability indicators tested using outer loadings values have also met the requirements because the outer loadings values of all indicators have been above 0.70.

Table 3. Measurement Model Evaluation Results

Construct	Indicator	CR	AVE	Outer Loadings	VIF
Brand Intention (BI)	BI1	0.871	0.694	0.864	2.089
	BI2			0.902	2.15
	BI3			0.722	1.311
Effort Expectancy (EE)	EE1	0.915	0.783	0.88	2.477
	EE2			0.886	2.464
	EE3			0.888	1.924
Facilitating Conditions (FC)	FC1	0.848	0.584	0.814	1.874
	FC2			0.746	1.948
	FC3			0.808	1.767
	FC4			0.68	1.204
Hedonic Motivation (HM)	HM1	0.987	0.814	0.876	1.665
	HM2			0.927	1.665
Habit (HT)	HT1	0.923	0.799	0.893	2.441
	HT2			0.863	2.128
	HT3			0.925	2.703
Performance Expectancy (PE)	PE1	0.882	0.653	0.827	1.948
	PE2			0.848	2.029
	PE3			0.815	1.746
	PE4			0.737	1.46
Performance Risk (PER)	PER1	0.897	0.746	0.758	1.569
	PER2			0.915	2.407
	PER3			0.909	2.378
Privacy Risk (PRR)	PRR1	0.918	0.79	0.864	1.806
	PRR2			0.921	3.628
	PRR3			0.881	3.026
Psychological Risk (PSR)	PSR1	1	1	1	1
Price Value (PV)	PV1	0.938	0.835	0.914	2.972
	PV2			0.89	2.48
	PV3			0.938	3.745
Social Influence (SI)	SI1	0.937	0.832	0.909	2.531
	SI2			0.923	2.994
	SI3			0.905	3.007
Trust in Medical Personnel (TP)	TP1	0.931	0.817	0.893	2.041
	TP2			0.914	3.658
	TP3			0.905	3.328

Next table 3, we tested discriminant validity using the Fornell-Larcker Criterion. The acceptance criterion for this method is that the square root of a construct's AVE must be greater than its correlation with other constructs. Table 4 shows the results of the Fornell-Larcker Criterion calculation.

Table 4. Fornell-Larcker Criterion

Construct	BI	EE	FC	HM	HT	PE	PER	PRR	PSR	PV	SI	TP
BI	0.833											
EE	0.324	0.885										
FC	0.467	0.618	0.764									
HM	0.523	0.384	0.448	0.902								
HT	0.64	0.299	0.299	0.471	0.894							
PE	0.508	0.684	0.635	0.586	0.426	0.808						
PER	-0.143	0.126	0.061	-0.01	-0.071	0.111	0.864					
PRR	-0.179	-0.063	-0.137	-0.226	-0.095	-0.099	0.641	0.889				
PSR	-0.126	-0.057	-0.018	0	-0.158	0.076	0.532	0.429	1			
PV	0.613	0.516	0.559	0.619	0.525	0.592	0.101	-0.155	-0.057	0.914		
SI	0.456	0.388	0.275	0.422	0.572	0.479	-0.043	-0.105	-0.323	0.368	0.912	
TP	0.523	0.346	0.551	0.615	0.365	0.532	-0.033	-0.205	0.047	0.598	0.245	0.904

Based on table 4 the Fornell-Larcker Criterion calculation results, it can be seen that no constructs violate discriminant validity. Next, a multicollinearity test using VIF values can be seen in Table 5.

Table 5. Multicollinearity Test (VIF Values)

Indicator	VIF
BI1	2.089
BI2	2.15
BI3	1.311
EE1	2.477
EE2	2.464
EE3	1.924
FC1	1.874
FC2	1.948
FC3	1.767
FC4	1.204
HM1	1.665
HM2	1.665

HT1	2.441
HT2	2.128
HT3	2.703
PE1	1.948
PE2	2.029
PE3	1.746
PE4	1.46
PER1	1.569
PER2	2.407
PER3	2.378
PRR1	1.806
PRR2	3.628
PRR3	3.026
PSR1	1
PV1	2.972
PV2	2.48
PV3	3.745
SI1	2.531
SI2	2.994
SI3	3.007
TP1	2.041
TP2	3.658
TP3	3.328

Based on Table 5, all indicators have VIF values below 5, so there is no multicollinearity problem in this research model. All tests in the measurement model evaluation indicate that both the constructs and their indicators have met the validity and reliability requirements, so the testing proceeds to the structural model evaluation stage. This testing begins with a bootstrapping process, which involves randomly resampling the original data repeatedly to allow for estimation of the research model without assuming a normal distribution of the data (Hair et al., 2017). In this study, 5,000 subsamples were taken. The results of the path coefficient and P-value calculations in this study are shown in Table 6.

Table 6. Path Coefficient and P-Value

Hypothesis	Path	Path Coefficients	P-Values	Conclusion
H1	EE -> BI	-0.143	0.134	Not Significant
H2	FC -> BI	0.256	0.041	Not Significant
H3	HM -> BI	0.019	0.866	Not Significant
H4	HT -> BI	0.337	0.009	Not Significant
H5	PE -> BI	0.112	0.348	Not Significant
H6	PER -> BI	-0.211	0.146	Not Significant
H7	PRR -> BI	0.077	0.443	Not Significant
H8	PSR -> BI	0.034	0.737	Not Significant
H9	PV -> BI	0.28	0.024	Not Significant
H10	SI -> BI	0.095	0.231	Not Significant
H11	TP -> BI	0.109	0.246	Not Significant

The p-value in Table 6 shows that this study supports hypotheses 2, 4, and 9, namely that facilitating conditions, habit, and price value are proven to have a significant influence on behavioral intention to adopt the Halodoc application. The influence of facilitating conditions, habit, and price value on behavioral intention is a positive influence as can be seen based on the path coefficient values for each of which are 0.256, 0.337, and 0.28, respectively. Therefore, this study shows that eight other hypotheses, including the extension factors of perceived risk and trust in medical personnel, do not have a significant influence on behavioral intention to adopt Halodoc in Indonesia. Therefore, the following is a regression equation based on the results of path coefficient calculations for constructs or factors that have a significant influence on behavioral intention to adopt Halodoc to be a prediction model for Halodoc and telemedicine service providers.

$$BI = 0.256FC + 0.337HT + 0.28PV$$

Based on the regression equation, habit is the factor with the greatest influence or correlation on brand intention to adopt Halodoc services, at 0.337. This indicates that the influence of habit is more significant and more effective than facilitating conditions and price value on behavioral intention to adopt Halodoc services. For example, each increase in habit will result in a 0.337 increase in behavioral intention. The structural model is also evaluated based on the coefficient of determination (R2), with values ranging from 0 to 1, indicating that the higher the R2 value, the greater the ability of the research model to explain the dependent variable, in this study, behavioral intention (Hair et al., 2016, 2017; Sarstedt et al., 2020). Table 7 below shows the results of the coefficient of determination calculation in this study.

Table 7. Coefficient of Determination (R^2)

Variable	R Square
BI	0.812

Table 7 shows the R2 value for the research model at 0.812. This indicates that 81.2% of the variance in the behavioral intention construct can be explained by the independent constructs: facilitating conditions, habit, and price value. However, 8.8% of the variance remains to be explained by other constructs not included in the current research model.

The results of this study indicate that only facilitating conditions, habit, and price value significantly influence behavioral intention to adopt Halodoc services. Other constructs, such as performance expectancy, effort expectancy, social influence, hedonic motivation, trust in medical personnel, and perceived risk, represented by the dimensions of performance risk, psychological risk, and privacy risk, did not show significant effects. These results were obtained based on the demographic characteristics of the sample: the majority of respondents, 62 out of 100, were aged 18–25, or Gen Z, while only a small proportion were from older age groups. The characteristics of this generation, commonly referred to as digital natives, indicate a tendency to consider usability and ease of adoption of technology as basic needs, thus less important determinants of adoption intentions (Jiao et al., 2023; Lu et al., 2023). Therefore, habit, which reflects a person's behavior or habits in using a technology, emerged as the most influential factor, consistent with evidence that repeated habits during the pandemic also strengthened the tendency to continue using telemedicine platforms (Lu et al., 2023; Octavius & Antonio, 2021).

Furthermore, facilitating conditions, which were shown to have a significant influence on behavioral intention, with a p-value of 0.041 and a path coefficient of 0.256, also indicated that infrastructure readiness and technical support were important factors in adopting telemedicine services, such as Halodoc. This is consistent with previous research that modified UTAUT2 for the telemedicine context and found that network access, device compatibility, and the availability of support services increased the likelihood of adopting telemedicine and other healthcare services (Schmitz et al., 2022). For Gen Z, who generally rely on seamless digital experiences, the availability of supporting facilities is essential and influences the decision to use a service continuously. Therefore, when a platform like telemedicine, such as Halodoc, can guarantee a stable technical experience, users are more likely to adopt the service as part of their routine.

Price value was also shown to have a significant influence, with a P-value of 0.024 and a path coefficient of 0.28. This indicates that the perception of economic value relative to the service's benefits plays a significant role in adoption decisions. These results align with previous research on mHealth, which emphasized the importance of perceived value, or price value in UTAUT2, in driving adoption intentions, particularly in developing countries where cost is an important, though not absolute, consideration (Hayat et al., 2024; Yan et al., 2021). However, for Gen Z, value can also include time efficiency, ease of access, and service flexibility. Therefore, pricing strategies that emphasize attractive packages, such as bundling, discounts, or other benefits, are likely to increase young users' intention to adopt Halodoc and similar telemedicine services.

An interesting finding in this study is that the construct of trust in medical personnel and each dimension of perceived risk performance, privacy, and psychological risk did not significantly influence behavioral intention to adopt Halodoc services. This suggests that in this study's sample, comprised of Gen Z in Indonesia, trust or perceived risk is irrelevant. This contrasts with previous research that suggests trust can be a significant determinant of intention to adopt healthcare technologies, such as telemedicine (Meylani et al., 2021; Zhan et al., 2024). Furthermore, this study supports Jiao et al. (2023), who explained that Gen Z tends to ignore or have a high tolerance for digital risks as long as they obtain clear functional benefits from digital technology, such as telemedicine. Therefore, in this study, with a predominantly Gen Z sample in Indonesia, reducing perceived risk or increasing trust is no longer a determinant of intention to adopt Halodoc services.

The R2 result of 0.812 shows that the model explains 81.2% of the variance in behavioral intention. This figure indicates that while many UTAUT2 constructs were insignificant in the context of this study, the combination of facilitating conditions, habit, and price value captured most of the relevant factors for the predominantly Gen Z respondent group in Indonesia. From a managerial perspective, these findings provide clear strategic direction for telemedicine service providers: to focus on strengthening user experience infrastructure, such as ensuring technical stability and service interoperability, developing features and promotions that encourage lifestyle or habitual use of Halodoc services through reminder systems, recurring subscriptions, and loyalty features, as well as pricing offers that highlight the overall benefits of using Halodoc telemedicine services.

However, limitations of this study include the relatively small sample size and the majority of Gen Z participants, which limits generalizability to a broader population, particularly older age groups who may weigh trust and perceived risk more strongly in their behavioral intention to adopt telemedicine services like Halodoc (Hayat et al., 2024). Furthermore, future research could conduct further studies using cross-regional and national samples and longer-term analysis to strengthen the findings. Thus, overall, this study shows a shift in the determinants of telemedicine service adoption. Among the Gen Z user population in Indonesia who are digital natives, facilitating conditions, habits, and price value are more important determinants of intention than other variables, including trust and perceived risk.

5. CONCLUSION

This study concludes that Halodoc service adoption is largely influenced by facilitating conditions, habit, and price value, with habit being the most influential factor in behavioral intention. This suggests that young users, predominantly Gen Z in Indonesia, tend to rely more on habitual patterns and considerations of perceived value than other factors, including trust and perceived risks. Factors that do not have a significant influence can be said to not affect users who are already digital natives and perceive telemedicine services like Halodoc as low-risk. With an R2 value of 0.812, this research model demonstrates high explanatory power and adds to the research contribution using UTAUT2, especially in populations with high digital literacy levels. This study also offers empirical insights into the shift in determinants of telemedicine service adoption, especially among Gen Z and in Indonesia.

6. SUGGESTIONS

Future research is expected to expand the demographic reach to include older users to examine the role of trust and perceived risk in telemedicine adoption. Further research is also expected to utilize a larger and broader sample size to gain deeper insights into technology adoption, such as telemedicine. Furthermore, longitudinal research can be conducted to observe how habits develop over time and how they influence behavioral intentions in daily use. To enhance the explanatory power of the research model, future research could add other constructs related to digital literacy or experience using digital technology services, such as Halodoc telemedicine in Indonesia.

7. REFERENCES

Anderson, L. A., & Dedrick, R. F. (2017). Development of the Trust in Physician Scale: A Measure to Assess Interpersonal Trust in Patient-Physician Relationships. *Psychological Reports*, *67*(3_suppl), 1091–1100. https://doi.org/10.2466/pr0.2017.67.3f.1091

Chrisdianti, G. O., Handayani, P. W., Azzahro, F., & Yudhoatmojo, S. B. (2023). Users' Intention to Use Mobile Health Applications for Personal Health Tracking. In *Journal of Information System)* (Vol. 19, Issue 1).

Dwivedi, Y. K., Rana, N. P., Jeyaraj, A., Clement, M., & Williams, M. D. (2019). Re-examining the Unified Theory of Acceptance and Use of Technology (UTAUT): Towards a Revised Theoretical Model. *Information Systems Frontiers*, *21*(3), 719–734. https://doi.org/10.1007/s10796-017-9774-y

Featherman, M. S., & Pavlou, P. A. (2020). Predicting e-services adoption: A perceived risk facets perspective. *International Journal of Human Computer Studies*, *59*(4), 451–474. https://doi.org/10.1016/S1071-5819(03)00111-3

Grewal, D., Gotlieb, J., & Marmorstein, H. (2021). The Moderating Effects of Message Framing and Source Credibility on the Price-Perceived Risk Relationship. *Journal of Consumer Research*, *21*(1), 145. https://doi.org/10.1086/209388

Hair, J. F., Hult, G. T., Ringle, C., & Sarstedt, M. (2017). A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM)—Joseph F. Hair, Jr., G. Tomas M. Hult, Christian Ringle, Marko Sarstedt. In *Sage*.

Hair, J. F., Sarstedt, M., Hopkins, L., & Kuppelwieser, V. G. (2016). Partial least squares structural equation modeling (PLS-SEM): An emerging tool in business research. *European Business Review*, *26*(2), 106–121. https://doi.org/10.1108/EBR-10-2013-0128

Hawa, T., Putri Paramita, E., Miharja, D. L., Trisula, Y., & Yohanes, S. (2023). PERSEPSI PENGGUNA APLIKASI HALODOC TERHADAP PENINGKATAN LITERASI KESEHATAN DI KOTA MATARAM. *Jurnal Ilmiah Mahasiswa Komunikasi Universitas Mataram*, *4*(2), 26–32.

Hayat, N., Al Mamun, A., Gao, J., Yang, Q., & Hussain, W. M. H. W. (2024). Envisaging the intention and adoption of electronic health applications among middle-aged and older adults: Evidence from an emerging economy. *Digital Health*, *10*. https://doi.org/10.1177/20552076241237499

Jiao, W., Chang, A., Ho, M., Lu, Q., Liu, M. T., & Schulz, P. J. (2023). Predicting and Empowering Health for Generation Z by Comparing Health Information Seeking and Digital Health Literacy: Cross-Sectional Questionnaire Study. *Journal of Medical Internet Research*, *25*, e47595. https://doi.org/10.2196/47595

Kuen, L., Schürmann, F., Westmattelmann, D., Hartwig, S., Tzafrir, S., & Schewe, G. (2023). Trust transfer effects and associated risks in telemedicine adoption. *Electronic Markets*, *33*(1). https://doi.org/10.1007/s12525-023-00657-0

Kurnia, F. (2021). Pengembangan Niat Adopsi Mobile Wallet: Integrasi Model UTAUT2 dengan Social Connectedness dan Culture. *Jurnal Rekayasa Sistem Industri*, *10*(2), 145–160. https://doi.org/10.26593/jrsi.v10i2.4374.145-160

Lu, H. H., Lin, W. S., Raphael, C., & Wen, M. J. (2023). A study investigating user adoptive behavior and the continuance intention to use mobile health applications during the COVID-19 pandemic era: Evidence from the telemedicine applications utilized in Indonesia. *Asia Pacific Management Review*, *28*(1), 52–59. https://doi.org/10.1016/j.apmrv.2022.02.002

Meylani, E., Waleleng, G. J., & Kalangi, J. S. (2021). *PENGARUH PENGGUNAAN APLIKASI HALODOC TERHADAP PEMENUHAN KEBUTUHAN INFORMASI KESEHATAN di KELURAHAN PANIKI BAWAH KECAMATAN MAPANGET KOTA MANADO*.

Ningsi, B. A., & Agustina, L. (2018). Analisis Kepuasan Pelanggan Atas Kualitas Produk dan Pelayanan Dengan Metode SEM-PLS. *Jurnal Statistika Dan Aplikasinya (JSA)*, *2*(2).

Octavius, G. S., & Antonio, F. (2021). Antecedents of Intention to Adopt Mobile Health (mHealth) Application and Its Impact on Intention to

Recommend: An Evidence from Indonesian Customers. *International Journal of Telemedicine and Applications*, *2021*. https://doi.org/10.1155/2021/6698627

Pappas, I. O., & Woodside, A. G. (2021). Fuzzy-set Qualitative Comparative Analysis (fsQCA): Guidelines for research practice in Information Systems and marketing. *International Journal of Information Management*, *58*. https://doi.org/10.1016/j.ijinfomgt.2021.102310

Prasetio, W., Widyarini, M., & Putrawangsa, D. (2025). Brand Intention, Brand Reliability, and Price on Repurchase Intention of Luxury Products in E-Commerce. *Jurnal Wawasan Manajemen*, *13*(2), 188–198. https://doi.org/10.20527/jwm.v13i2.341

Ratan, R., Earle, K., Rosenthal, S., Hua Chen, V. H., Gambino, A., Goggin, G., Stevens, H., Li, B., & Lee, K. M. (2021). The (digital) medium of mobility is the message: Examining the influence of e-scooter mobile app perceptions on e-scooter use intent. *Computers in Human Behavior Reports*, *3*(December 2020), 100076. https://doi.org/10.1016/j.chbr.2021.100076

Rauschnabel, P. A., He, J., & Ro, Y. K. (2018). Antecedents to the adoption of augmented reality smart glasses: A closer look at privacy risks. *Journal of Business Research*, *92*, 374–384. https://doi.org/10.1016/j.jbusres.2018.08.008

Sarstedt, M., Ringle, C. M., & Hair, J. F. (2020). Handbook of Market Research. In *Handbook of Market Research* (Issue September). https://doi.org/10.1007/978-3-319-05542-8

Schmitz, A., Díaz-Martín, A. M., & Yagüe Guillén, M. J. (2022). Modifying UTAUT2 for a cross-country comparison of telemedicine adoption. *Computers in Human Behavior*, *130*. https://doi.org/10.1016/j.chb.2022.107183

Stone, R. N., & Grønhaug, K. (2023). Perceived Risk: Further Considerations for the MarketingDiscipline. *European Journal of Marketing*, *27*(3), 39–50. https://doi.org/10.1108/03090569310026637

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2020). User Acceptance of Information Technology: Toward a Unified View. *Management Information Systems Quarterly*, *27*(3), 425–478. https://doi.org/10.1016/j.inoche.2016.03.015

Venkatesh, V., Thong, J. Y. L., & Xu, X. (2022). Consumer Acceptance and Use of Information Technology: Extending the Unified Theory of Acceptance and Use of Technology. *Management Information Systems Quarterly*, *36*(1), 157–178. https://doi.org/10.1109/MWSYM.2015.7167037

Yan, M., Filieri, R., Raguseo, E., & Gorton, M. (2021). Mobile apps for healthy living: Factors influencing continuance intention for health apps. *Technological Forecasting and Social Change*, *166*. https://doi.org/10.1016/j.techfore.2021.120644

Zhan, X., Abdi, N., Seymour, W., & Such, J. (2024). Healthcare Voice AI Assistants: Factors Influencing Trust and Intention to Use. *Proceedings of the ACM on Human-Computer Interaction*, *8*(CSCW1). https://doi.org/10.1145/3637339

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