Hybrid Model Based on Technology Acceptance Model (TAM) & Information System Success Model (ISSM) in Analyzing the Use of E-Health

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Abstract. Electronic health or commonly known as e-health is defined as the use of information and communication technology in supporting the health and health-related fields. The outbreak of the Covid-19 virus in 2019 has led to a massive increase in the use of e-health, therefore it is important to know how users accept e-health. To analyze e-health acceptance, we combined the extended TAM model with enhanced care and increased accessibility and ISSM. A total of 121 data were collected using a structured questionnaire. The data that has been collected was analyzed using PLS-SEM. From the tests that have been carried out, it is known that the enhanced care, perceived usefulness, perceived ease of use, attitude, information quality, satisfaction have a significant influence on usage intentions, while the increased accessibility, net benefit, service quality, and system quality factors have no significant effect on intention to use.

1 Introduction

On December 31, 2019, the coronavirus disease 2019 (Covid-19) was officially reported in Wuhan, Hubei Province, China and on March 11, 2020 the World Health Organization (WHO) officially declared that Covid-19 had become a global pandemic. The Covid-19 pandemic has become a challenge in all aspects of human life, especially in the health care sector. The pandemic has led to rapid digitalization of the healthcare sector due to the urgent need to reduce exposure to Covid-19, while still supporting patient-doctor interactions and at the same time reducing the spread of the virus. One solution that can be applied to deal with this problem is to use an electronic health (e-health) application to support patient health care and at the same time control the spread of Covid-19 [1][2][3].

Electronic health or commonly known as e-health is defined as the use of information and communication technology in supporting the health sector and related to health (WHO, 2005). E-health allows for communication without face-to-face interaction between patients and doctors for medical diagnosis and treatment [4]. Other studies also find a remarkable increase in the adoption of e-health worldwide due to the Covid-19 pandemic [5][6]. Studies

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in Korea also found that people tend to use e-health services during a pandemic to get medical advice and healing during periods of self-isolation [3]. Therefore, it is important to understand how e-health is accepted by users.

User acceptance of e-health can be analyzed by applying technology acceptance theory such as the Technology Acceptance Model (TAM) [7] or updating the DeLone & McLean Information System Success Model (ISSM) [8]. TAM itself is a model developed by Davis [9] which can be used to analyze what factors can affect a technology or information system. Extended TAM is a modification of the TAM model which adds an increased accessibility variable and enhanced as an external variable [7]. In its application to analyze telehealth, this model is able to explain what factors can influence the intention to use telehealth [7]. It is also found that TAM is the most suitable model used to explain end user behavior in the field of using information technology for health [10]. Two fundamental variables used in TAM are perceived usefulness (PU) and perceived ease of use (PEOU). PU indicates the level of consumer confidence in using a technology that can improve user performance [7]. While PEOU indicates the level of consumer confidence in the use of a technology will facilitate the effort spent [7]. On the other hand, ISSM is a model developed by DeLone & McLean in 1992 which was later updated in 2003 which is now known as updated D&M ISSM [11]. D&M ISSM consists of six variables, namely system quality (SyQ), service quality (SQ). information quality (IQ), intention to use (IU), satisfaction (S), and net benefit (NB). This model does not measure the six d measurement of success measures independently, but overall measures which factors influence other factors.

TAM usage to analyze a technology will be stronger if it is added with at least two other variables [12]. The addition of increased accessibility and enhanced care in research related to telehealth has been shown to have a significant effect on PU [7], where the results of this study are in line with previous research [13][14]. The integration of the TAM model into the ISSM model has also been shown to provide appropriate antecedents for usage intentions because TAM has a stronger theoretical background to predict behavioral intentions [14]. Other research on information systems in the academic field also found that ISSM was proven to add explanations to the TAM model by providing a different point of view, where this had an impact on the better model and analysis produced [16][20]

2 Literature Review

Previous research related to evaluating e-health services has often been done before and has been increasing since the outbreak of the Covid-19 virus. Before the Covid-19 outbreak, e-health and related approaches had been developed in stages but there was no significant development [21]. Both medical personnel and patients are comfortable with conventional mechanisms and show little interest in using e-health [21]. Many health institutions avoid implementing e-health and do not realize the many benefits it offers [21]. A study by the WHO Global Observatory for Health found that e-health resources are very useful in 70% of non-OECD (Organization for Economic Co-operation and Development) countries and with proper implementation of e-health, it will not only provide protection against Covid-19 but can also overcome the world after the Covid-19 pandemic [3]. Studie by Gu also found that the use of e-health can optimize profits, save budgets, increase efficiency, better health services, and can improve patient health [17].

E-health and similar systems have been widely evaluated using previous technology acceptance theories [7][8] [17][18]. Research conducted by Al-Fadhli et al., found that the ISSM model was proven to be able to reveal factors that could influence the intention to use [8]. However, this study only uses the ISSM model without adding other variables, even though the ISSM model is a model that has a weak basic theory in predicting the intention to use an information system or information technology [14] Then Gu et al, analyzed e-health

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by integrating the UTAUT model with several additional variables such as trust, privacy, task technology fit (TTF), and Personal Innovativeness (PI) [17]. This study resulted in a better model than the general UTAUT model by providing further understanding on social, cultural, and appropriate aspects of technology and the task of analyzing the adoption of e-health. However, the use of UTAUT is more suitable to be used to analyze a system or information technology that is used within the scope of the organization or is mandatory [14]. On the other hand, An et al., adapted the TAM model to pandemic conditions by adding EC, IA, PD, CA to the proposed model [7]. The use of a modified TAM is the most suitable model to be used to explain end-user behavior in the field of using information technology for health compared to other models [10]. Another study also revealed that ISSM added an explanation to the TAM model by providing a different point of view, where this had an impact on the better model and analysis produced [15][20]. The combination of the TAM model with ISSM provides a stronger theoretical background to BIU and provides a perspective on the technical success, semantics, and effectiveness of a system [14] Previously, the combination of TAM & ISSM has been used before to measure AIS [20], but it is still unclear how the impact of this combination will have if it is used to analyze e-health.

3 Theoretical Backgrounds

3.1 Electronic Health (E-Health)

The World Health Organization (WHO) defines E-Health as the cost-effective and secure use of information and communication technologies to support health and health-related fields, including health care services, health surveillance, health literature, and health education, knowledge and research (WHO, 2021). E-health enables transmission and information management related to patient health care and contributes in improving patient health and the performance of medical practitioners [20]. E-health applications are not only gaining popularity in health centers but are also accepted for home care and for information seeking by the public [21]. E-health includes various forms of health care communication, such as telemedicine, internet-based examinations and interviews, online therapy, and the use of applications or software to track and collect medical information.

3.2 Increased Accessibility (IA)

Accessibility is a belief that a health care system has performed it’s function for health care recipients and health care providers. Increasing accessibility is one of the key factors in the success of a health service [7]. Access within the scope of health care includes interactions between human resources, environment, systems, and institutions, where these components have an important role in health care performance.

3.3 Enhanced Care (EC)

Enhanced care is a belief how e-health can improve patients health care that they receive. E-health allows patients to consult with health professionals and allows for early detection of a disease [7]. The use of e-health can increase the efficiency and effectiveness of health care in the context of costs incurred compared to traditional visits. In previous studies, it was also shown that the use of e-health was proven to be effective in helping psychological treatment[7].

3.4 Technology Acceptance Model (TAM)

Technology Acceptance Model (TAM) is a model that can be used in analyzing the factors that influence the acceptance of a technology or an information system [9]. TAM is adapted from Theory of Reasoned Action (TRA) by Fishbein & Ajzen which is devoted to the acceptance of a technology or information system [22]. TAM assumes that Perceived

Ease of Use (PEOU) and Perceived Usefulness (PU) are of major relevance in the acceptance of a technology [9]. Perceived Usefulness (PU) is defined as the degree to which users have confidence that the use of a particular system or technology can improve user performance [9]. Meanwhile, Perceived Ease of Use (PEOU) is the level of user confidence in using a certain technology or system that will facilitate business [9]. In line with TRA, TAM stated that the use of technology is based on the Behavioral Intention to Use (BI) variable which is influenced by the user's Attitude Toward Using (A) as well as PU and PEOU.

3.5 Information System Success Model (ISSM)

The Information System Success Model (ISSM) is a model developed by DeLone & McLean in 1992 [8]. This model consists of six latent variables, namely, System Quality, Information Quality, Individual Impact, System Usage, Organizational Impact, and User Satisfaction [11]. Historically, the initial ISSM model was often criticized for lack of variables in the model and was considered unsuitable for use in analyzing the success of information systems, then an updated ISSM was proposed in 2003 which is a modification of the previous model [18]. Updated ISSM added Service Quality variables that are used to measure user behavior, Intention to Use as well as Individual Impact and Organizational Impact as Net Benefit [18].

4 Partial Least Square - Structural Equation Modeling (PLS-SEM)

Partial Least Square-Structural Equation Modeling (PLS-SEM) is a method developed by Wold and Lohmoller [23]. PLS-SEM or Variance Based SEM is a type of SEM that only allows a unidirectional relationship between variables [24]. In prediction research, PLS-SEM is more suitable to be used compared to Covariance-based SEM, because Covariance-based SEM is better used to test existing theories and confirmation.

In addition, PLS-SEM is also a suitable method for research that has a limited number of [25]. In PLS-SEM, the test model is based on non-parametric predictive measurements, which means that data sample is allowed to not normally distributed, small sample size, and tends to be simple [26].

4.1 Proposed Model

The model proposed in this study can be seen in Figure 1 below.

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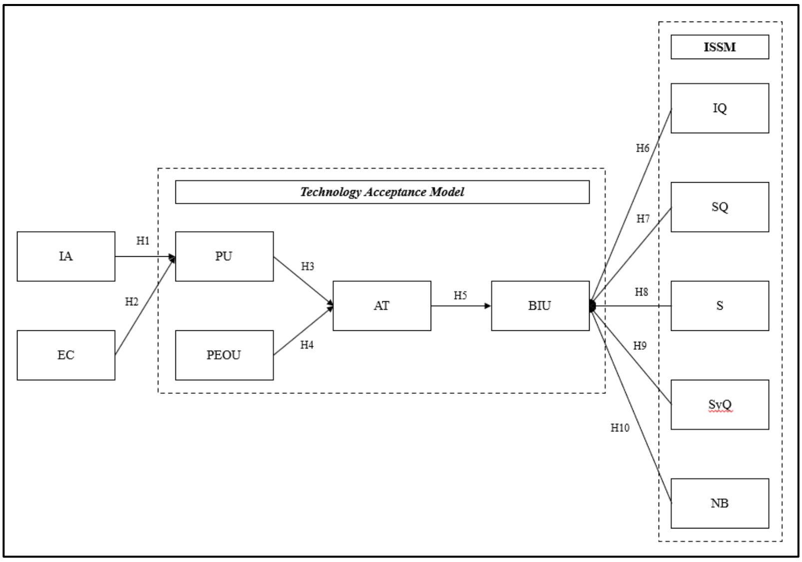

Fig. 1. The Proposed Model

H1. Increased accessibility has a positive and significant impact on the perceived usefulness of e-health.
H2. Enhanced care has a positive and significant impact on the perceived usefulness of e-health
H3. Perceived usefulness has a positive and significant impact on the perceived usefulness of e-health
H4. Perceived ease of use has a positive and significant impact on the perceived usefulness of e-health
H5. Attitude has a positive and significant impact on the behavioral intention to use e-health
H6. Information quality has a positive and significant impact on the behavioral intention to use e-health
H7. Service quality has a positive and significant impact on the behavioral intention to use e-health
H8. Satisfaction has a positive and significant impact on the behavioral intention to use e-health
H9. System quality has a positive and significant impact on the behavioral intention to use e-health
H10. Net Benefit has a positive and significant impact on the behavioral intention to use e-health

5 Methodology

5.1 Data Collection

Data was collected using an instrument in the form of a structured questionnaire. The questionnaire was distributed on social media (Instagram and Twitter) and messenger applications (Whatsapp). It contains demographic data such as name, occupation, education, e-health used, and domicile as well as statements related to variables used in the study totaling 38 statements.

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5.2 Data Analysis

In PLS-SEM there are two stages of testing, namely testing the outer model and then continuing with testing the inner model. The outer model test was conducted to determine the validity and reliability of the data used in the research. In conducting the validity test, there are two tests that must be carried out, namely testing with convergent validity and testing with discriminant validity. Convergent validity testing is done using the Average Variance Extracted (AVE) value or the outer loading value or both. The expected AVE value in the convergent validity test is greater than 0.5 [35], if there is an AVE value that does not meet the criteria, the latent variable must also be removed from the model. Meanwhile, in the convergent validity test with outer loading, the expected value is greater than 0.7 in confirmatory research and greater than 0.5 in development research and can use a scale of 0.5 – 0.6 [35][36], where if there is an outer loading value that is smaller than 0.4, it must be removed from the model [37]. The discriminant validity test is carried out by cross loading or by comparing the AVE roots with the latent variable correlations or it can be both. In the discriminant validity test by comparing the roots of AVE with the latent variable correlation, the value of the square root of the AVE must be greater than the value of the latent variable correlation, this indicates that the latent variable has a good discriminant validity value [38]. The data reliability test was carried out by looking at the value of Cronbach's alpha and composite reliability. The minimum value of cronbach's alpha is 0.7. If there is a value that does not meet the criteria for an indicator or variable in the outer model test, then the indicator or variable is deleted and recalculation is carried out until all remaining indicators and variables meet the test criteria.

After all variables and indicators meet the minimum test criteria, the next step is testing the inner model. The inner model test is used to see the relationship between latent variables. In testing the inner model, there are three things that must be done, namely, R-Square testing, Q-Square testing, and hypothesis testing which includes testing the P-Value, T-Statistic and Original Sample values. There are three categories of R-Square values, namely substantial, moderate, and weak. R-Square values of more than 0.67 fall into the strong category, the value 0.33 into the moderate category, and 0.19 into the weak category [35]. Q-Square value that is more than zero (0) indicates that the model has predictive relevance, whereas if the value of Q-Square is less than zero (0) then it indicates that the model has no predictive relevance. After that, hypothesis testing is used to explain how big the relationship and the influence of latent variables on other latent variables. The Original Sample value shows how the direction of the relationship of a latent variable is, whether the relationship is positive or negative. A relationship is said to have a positive relationship if it has a positive Original Sample value or more than zero, and vice versa if the Original Sample value is negative then the relationship between the variables is negative [36]. A hypothesis will be accepted if it has a P-Value value less than 0.05. A relationship will be said to be significant if the resulting value is more or equal to the T-Table value (T-Statistic >= 1.96). The relationship is said to be insignificant if the resulting T-Statistic value is less than the T-Table value [36]. From the data testing that has been carried out, it can then be concluded whether the proposed hypothesis is accepted or not, which then the results of the hypothesis test can be used for the development of e-health services in the future.

6 Result and Discussion

From a total of 121 respondent data obtained, it is known that 68.6% of respondents are female, 44.62% of respondents are students with 60.33% having an undergraduate education level. From the resulting data, it is also known that around 62.80% of respondents live in Central Java, and 75,2% respondents have used Halodoc.

After the data has been collected, the data is then tested for the outer model testing. The outer model test consists of testing the validity of the data and testing the reliability of the data. In testing the validity of the data, two types of tests were carried out, namely testing using convergent validity and testing with discriminant validity. In testing the validity of the data with convergent validity, testing is carried out using the outer loading and Average Variance Extracted (AVE) values. The results of the convergent validity test using outer loading can be seen in Table 1, while the results of the convergent validity test with AVE can be seen in Table 2.

Table 1. Convergent Validity Test with Outer Loading

Indicators	Outer Loading	Description	Indicators	Outer Loading	Description
AT1	0,897	Accepted	NB2	0,956	Accepted
AT2	0,918	Accepted	NB3	0,966	Accepted
AT3	0,915	Accepted	NB4	0,967	Accepted
AT4	0,910	Accepted	PEOU1	0,824	Accepted
BI1	0,882	Accepted	PEOU2	0,821	Accepted
BI2	0,879	Accepted	PEOU3	0,923	Accepted
BI3	0,856	Accepted	PEOU4	0,835	Accepted
EC1	0,891	Accepted	PU1	0,947	Accepted
EC2	0,841	Accepted	PU2	0,958	Accepted
EC3	0,880	Accepted	PU3	0,933	Accepted
IA1	0,871	Accepted	S1	0,923	Accepted
IA2	0,852	Accepted	S2	0,918	Accepted
IA3	0,740	Accepted	S3	0,846	Accepted
IA4	0,843	Accepted	SQ1	0,940	Accepted
IQ1	0,918	Accepted	SQ2	0,946	Accepted
IQ2	0,958	Accepted	SQ3	0,914	Accepted
IQ3	0,941	Accepted	SyQ1	0,917	Accepted
IQ4	0,872	Accepted	SyQ2	0,908	Accepted
NB1	0,529	Accepted	SyQ3	0,872	Accepted

Based on Table 1 it can be seen that all indicators have an outer loading value of more than 0.5, with the smallest value of 0.529 belonging to the NB1 indicator and the largest value being owned by the NB4 indicator with a value of 0.967. From the results of these calculations, no indicators were abolished and no re-calculation was necessary.

Table 2. Convergent Validity Test with AVE

Indicators	AVE	Description	Indicators	AVE	Description
AT	0,828	Accepted	PEOU	0,725	Accepted
BI	0,761	Accepted	PU	0,895	Accepted
EC	0,758	Accepted	S	0,804	Accepted
IA	0,686	Accepted	SQ	0,871	Accepted
IQ	0,852	Accepted	SyQ	0,808	Accepted
NB	0,765	Accepted			

From Table 2 it can be seen that all latent variables have an AVE value of more than 0.5, with the smallest AVE value being owned by the latent variable IA of 0.686 and the largest AVE value being owned by the latent variable PU of 0.895.

Testing the validity of the data with discriminant validity was tested using the cross loading value and the comparison of RAVE with the latent variable correlations. The results of the test with cross loading can be seen in Table 3, while the test with RAVE and latent variable correlations can be seen in Table 3.

Table 3. Discriminant Validity Test with Cross Loading

	AT	BI	EC	IA	IQ	NB	PEOU	PU	S	SQ	SyQ
AT1	**0.897***	0.779	0.671	0.746	0.741	0.576	0.716	0.662	0.799	0.689	0.704
AT2	**0.918***	0.822	0.683	0.738	0.715	0.576	0.723	0.723	0.809	0.692	0.669
AT3	**0.915***	0.764	0.704	0.673	0.768	0.696	0.732	0.746	0.778	0.738	0.751
AT4	**0.910***	0.756	0.767	0.712	0.756	0.730	0.689	0.826	0.829	0.781	0.733
BI1	0.801	**0.882***	0.762	0.776	0.757	0.660	0.653	0.829	0.844	0.747	0.747
BI2	0.707	**0.879***	0.572	0.593	0.694	0.542	0.596	0.672	0.672	0.598	0.610
BI3	0.730	**0.856***	0.559	0.755	0.705	0.470	0.663	0.590	0.688	0.618	0.618
EC1	0.645	0.593	**0.891***	0.744	0.553	0.528	0.517	0.762	0.635	0.663	0.543
EC2	0.742	0.768	**0.841***	0.712	0.737	0.594	0.601	0.739	0.743	0.713	0.700
EC3	0.641	0.544	**0.880***	0.639	0.538	0.533	0.600	0.734	0.614	0.598	0.542
IA1	0.713	0.745	0.663	**0.871***	0.708	0.506	0.666	0.639	0.683	0.656	0.674
IA2	0.797	0.728	0.739	**0.852***	0.679	0.635	0.580	0.774	0.751	0.706	0.663
IA3	0.462	0.576	0.585	**0.740***	0.517	0.370	0.535	0.553	0.493	0.486	0.520
IA4	0.590	0.636	0.654	**0.843***	0.568	0.438	0.543	0.631	0.632	0.651	0.569
IQ1	0.745	0.784	0.596	0.720	**0.918***	0.615	0.679	0.652	0.712	0.762	0.799
IQ2	0.800	0.806	0.702	0.749	**0.958***	0.666	0.702	0.701	0.739	0.855	0.832
IQ3	0.774	0.792	0.660	0.692	**0.941***	0.623	0.694	0.680	0.726	0.797	0.838
IQ4	0.696	0.649	0.623	0.604	**0.872***	0.609	0.677	0.602	0.673	0.773	0.811
NB1	0.384	0.411	0.342	0.428	0.351	**0.529***	0.361	0.386	0.435	0.362	0.376
NB2	0.668	0.604	0.595	0.558	0.642	**0.956***	0.550	0.629	0.698	0.673	0.644
NB3	0.678	0.590	0.598	0.535	0.654	**0.966***	0.563	0.635	0.669	0.700	0.671
NB4	0.694	0.615	0.632	0.566	0.676	**0.967***	0.598	0.672	0.706	0.722	0.685
PEOU1	0.550	0.604	0.574	0.607	0.624	0.447	**0.824***	0.550	0.560	0.592	0.676
PEOU2	0.612	0.552	0.458	0.466	0.513	0.412	**0.821***	0.513	0.525	0.478	0.540
PEOU3	0.751	0.689	0.613	0.653	0.708	0.518	**0.923***	0.620	0.636	0.634	0.763
PEOU4	0.736	0.637	0.583	0.647	0.674	0.650	**0.835***	0.618	0.676	0.705	0.641
PU1	0.733	0.719	0.829	0.746	0.638	0.627	0.586	**0.947***	0.752	0.688	0.626
PU2	0.757	0.750	0.822	0.731	0.659	0.669	0.633	**0.958***	0.765	0.713	0.666
PU3	0.815	0.812	0.778	0.773	0.732	0.626	0.705	**0.933***	0.807	0.709	0.720
S1	0.831	0.808	0.707	0.736	0.713	0.643	0.710	0.771	**0.923***	0.720	0.687

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	AT	BI	EC	IA	IQ	NB	PEOU	PU	S	SQ	SyQ
S2	0.787	0.756	0.677	0.703	0.699	0.682	0.634	0.727	**0.918***	0.737	0.657
S3	0.756	0.711	0.666	0.665	0.667	0.638	0.554	0.704	**0.846***	0.697	0.645
SQ1	0.772	0.745	0.719	0.716	0.855	0.711	0.699	0.684	0.766	**0.940***	0.796
SQ2	0.741	0.689	0.720	0.731	0.806	0.656	0.682	0.684	0.772	**0.946***	0.783
SQ3	0.715	0.676	0.676	0.689	0.752	0.650	0.613	0.717	0.702	**0.914***	0.743
SyQ1	0.683	0.656	0.606	0.631	0.771	0.603	0.689	0.614	0.675	0.754	**0.917***
SyQ2	0.670	0.686	0.584	0.642	0.824	0.599	0.704	0.589	0.610	0.736	**0.908***
SyQ3	0.758	0.701	0.648	0.711	0.795	0.669	0.688	0.707	0.708	0.747	**0.872***

It can be seen in Table 3 above that all indicators have the highest loading value when paired with the underlying latent variables, this indicates that these latent variables are able to predict indicators in their block better than other latent variables. Therefore, it can be concluded that the indicator pairing with the underlying latent variables is valid.

Table 4. Discriminant Validity Test with Latent Variable Correlations

	AT	BI	EC	IA	IQ	NB	PEOU	PU	S	SQ	SyQ
AT	**0,910***										
BI	0,857	**0,872***									
EC	0,776	0,729	**0,871***								
IA	0,788	0,816	0,803	**0,828***							
IQ	0,818	0,825	0,699	0,752	**0,923***						
NB	0,708	0,643	0,634	0,601	0,681	**0,875***					
PEOU	0,788	0,732	0,656	0,701	0,745	0,603	**0,851***				
PU	0,813	0,804	0,856	0,793	0,715	0,677	0,679	**0,946***			
S	0,884	0,847	0,762	0,783	0,773	0,729	0,709	0,820	**0,897***		
SQ	0,797	0,754	0,756	0,763	0,864	0,721	0,713	0,744	0,801	**0,933***	
SyQ	0,784	0,759	0,683	0,737	0,887	0,695	0,772	0,709	0,740	0,830	**0,899***

From Table 4 it can be seen that the square root value of AVE for all latent variables is higher than the correlation value between latent variables. This indicates that all latent variables have met the discriminant validity criteria and have good discriminant validity values.

After testing the validity of the data, then testing the reliability of the data. Data reliability testing is done by assessing the value of Cronbach's alpha and the value of composite reliability. Cronbach's alpha value and the value of composite reliability can be seen in the table.

Table 5. Reliability Test with Cronbach's Alpha

Indicators	*Cronbach's Alpha*	Description
AT	0,931	Accepted
BI	0,843	Accepted
EC	0,840	Accepted
IA	0,847	Accepted
IQ	0,942	Accepted
NB	0,879	Accepted
PEOU	0,873	Accepted
PU	0,941	Accepted
S	0,877	Accepted
SQ	0,926	Accepted
SyQ	0,881	Accepted

From the calculations that have been done, it can be seen in Table 5, that the value of Cronbach's Alpha of all latent variables in the model is more than 0.7, with the lowest Cronbach's Alpha owned by the latent variable EC with a value of 0.840 and the highest Cronbach's Alpha owned by the latent variable IQ with a value of 0.942. This means that respondents' answers to all indicators are consistent and stable, so that the resulting data is reliable.

Table 6. Reliability Test with Composite Reliability

Indicators	*Composite Reliability*	Description
AT	0,951	Accepted
BI	0,905	Accepted
EC	0,904	Accepted
IA	0,897	Accepted
IQ	0,958	Accepted
NB	0,925	Accepted
PEOU	0,913	Accepted
PU	0,962	Accepted
S	0,925	Accepted
SQ	0,953	Accepted
SyQ	0,927	Accepted

From the results of composite reliability in Table 6, it can be seen that the composite reliability value of all latent variables is more than 0.7 with the lowest value being owned by the latent variable IA with a value of 0.897 and the highest being owned by the latent variable PU with a value of 0.962. This indicates that the data can be trusted to be processed further.

After all variables and indicators meet the minimum test criteria, the next step is testing the inner model. In testing the inner model, there are three things that must be done, namely, R-Square testing, Q-Square testing, and hypothesis testing which includes testing the P-Value, T-Statistic and Original Sample values. the results of the r-square can be seen in the table 7, the results of the q-square can be seen in the table 8, the results of the hypothesis testing can be seen in the table 9.

Table 7. R-Square Test

Indicators	*R-Square*	Description
AT	0,764	Substantial
BI	0,811	Substantial
PU	0,764	Substantial

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Based on the R-Square calculations that have been done and shown in Table 7, it is known that the BI variable has the highest R-Square value with a value of 0.811 which means that 81.1% of the influence received by the BI latent variable is influenced by the latent variables AT, S, IQ, SQ, SyQ, and NB while the rest is the influence of other variables outside the research model. While the latent variable AT has an R-Square value of 0.763, which indicates that 76.3% of the influence received by the latent variable AT is influenced by the latent variables PU and PEOU, while the rest is the influence of other variables outside the model. And lastly, the endogenous variable PU has an R-Square value of 0.772, which means that only 77.2% of the influence received by the latent variable PU is influenced by latent variables IA and EC, while the rest is the influence of other variables outside the proposed model. in research.

Table 8. Q-Square Test

Indicators	*Q-Square*	Description
AT	0,581	Predictive
BI	0,550	Predictive
PU	0,643	predictive

From Table 8 it is known that all endogenous latent variables have a positive Q-square value, with the highest Q-square value owned by the PU latent variable of 0.643, then the latent variable AT with a Q-square value of 0.581, and the smallest latent variable BI with a Q-Square value of 0.550. This indicates that all endogenous latent variables in the model proposed in this study have predictive relevance.

Table 9. Hypothesis Testing

Hypothesis	*Original Sample*	*T-Statistic*	*P-Value*	Description
AT -> BI	0.308	2.117	0.035	Accepted
EC -> PU	0.617	5.852	0.000	Accepted
IA -> PU	0.298	2,663	0.008	Accepted
IQ -> BI	0.412	3.30	0.001	Accepted
NB -> BI	-0.055	0.749	0.454	Rejected
PEOU -> AT	0.437	4.151	0.000	Accepted
PU -> AT	0.516	4.457	0.000	Accepted
S -> BI	0.397	3.290	0.001	Accepted
SQ -> BI	-0.124	1.274	0.203	Rejected
SyQ -> BI	-0.000	0.004	0.997	Rejected

As can be seen in Table 9, H1, H2, H3, H4, H6, H7, H8 have a positive original sample value, a t-statistic value of more than 1.96, and a p-value of less than 0.05 which means that indicates that the hypothesis is accepted, this indicates that the exogenous variables in the relationship have a positive and significant influence on the endogenous variables. Meanwhile, for H5, H9, and H10, the hypothesis is rejected because the original sample value is negative, the t-statistic is less than 1.96, and the p-value is more than 0.05, this indicates that the exogenous variables in the relationship have a negative and insignificant effect to the endogenous variables.

According to the results of calculations that have been carried out, IA and EC have a positive and significant influence on PU. The results of this calculation corroborate the findings of An et al., [7] who examined the effect of IA and EC on telehealth in Korea and also corroborate the research by Nomura et al., who found that the efficacy of using e-health was not inferior to the method face-to-face consultation (clinical visits) [39]. E-health can be a viable alternative because it shows no lower efficacy than standard face-to-face. Access to health care facilities is also becoming easier which results in the opportunity to receive the right health services in situations where they are needed.

This study also reveals that the fundamental variables of TAM, namely PU and PEOU, have a positive and significant effect on AT, where these results strengthen the research conducted by An et al., [7]. Purwanto & Budiman also confirmed that the PU and PEOU perceived by individuals have a positive relationship with the attitude (AT) of users towards the adoption of e-health services [40]. Zobair et al., also claim that PU is an important predictor in BIU to use e-health services, as a result, if users think that e-health is useful, users tend to use it[41]. Wilson and Lankton in their research on e-health found that PU and PEOU are significant antecedents to BIU [42]. This also indicates that individuals can show higher usage intentions to use e-health if they understand the usefulness and ease of use of the information system used. Therefore, the more users who find e-health useful and easy, users will have a higher intention to use e-health. On the other hand, the relationship between AT and BIU proved to have a positive and significant impact. Zayyad and Toycan also claim that AT is one of the factors that has a significant impact on the intention to use e-health [43].

In the variables of the ISSM model, three rejected hypotheses were found, namely H7, H9, and H10. These results are inversely proportional to the results of research conducted by Al-Fadhli et al., which found a positive influence given by SQ, SyQ, and NB on BIU [8]. However, research conducted in Jordan, which is a developing country such as Indonesia, found that cost did not significantly affect the adaptation of e-health use (Faqih & Jaradat, 2015). This is probably based on users who do not feel the benefits of e-health which include saving time, costs, and effort spent in obtaining health services. In addition, users also feel that the services provided by e-health.

6.1 Theoretical Implications

The results of this study have contributed to the theory used as well as better system management. This study provides a fundamental contribution to information systems research on the scope of e-health use in Indonesia and also this study uses a combination of TAM & ISSM models as well as IA and EC variables. So far, studies that examine e-health by combining TAM & ISSM are still quite rare, while the research conducted by Hidayah et al., (2020) uses the TAM & ISSM hybrid model to analyze mobile-based academic information systems. By researching e-health using the TAM & ISSM model, of course this study contributes to the increase in the health literature and literature related to technology acceptance. In addition, this research also contributes to finding factors that can influence the use of e-health in Indonesia which of course can be used as a benchmark or reference source for future research related to e-health. This study also confirms the use of the TAM & ISSM hybrid model in the context of health care (e-health) which has never been done before.

6.2 Practical Implications

The findings of this study also provide practical guidance for the successful use of e-health in Indonesia. This will certainly be very beneficial for designers and providers of e-health technology to assist them in understanding the challenges and problems in implementing a successful e-health technology. This study also comprehensively explores the factors that influence users' intention to use e-health.

7 Conclusion

This study was conducted as an effort to determine the factors that can influence users in using e-health services. Therefore, the tam and issm models, as well as external variables such as ia and ec are integrated to analyze the intention to use e-health services. This study also uses the pls-sem method which is used to process respondent data. From the calculations that have been carried out, it shows that 81.1% intention to use e-health services is influenced by at, pu, peou, ia, ec, s, iq, sq, syq, and nb and also found the q-square value of endogenous latent variables that used is positive which indicates that the endogenous latent variable has predictive relevance. Thus, theoretically, this study confirms that the integration of the tam and issm models as well as the ia and ec variables is adequate. Meanwhile, based on the hypothesis testing that has been carried out, it was found that three of the 10 proposed hypotheses were rejected, namely h7, h9, and h10. By doing this research, this research contributes to the information systems literature.

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