An Empirical Study of Student Acceptance toward SaaS-Based Academic Information System: an extended UTAUT Model

Abd Rahman
Department of Information Systems
Institut Teknologi Sepuluh Nopember
Surabaya, Indonesia
rahmanakademika777@gmail.com

Reny Nadlifatin*
Department of Information Systems
Institut Teknologi Sepuluh Nopember
Surabaya, Indonesia
reny@its.ac.id , reny.nadlifatin@gmail.com

Satria Fadil Persada
Entrepreneurship Department, BINUS Business School Undergraduate Program, Bina Nusantara University, Jakarta, Indonesia
satria.fadil@binus.ac.id

Abstract

Software as a Service (SaaS)-based academic information system has become a new trend in system procurement in universities, particularly in Indonesia. With the various advantages of SaaS-based academic information systems, many universities have decided to switch to this service model. Factors influencing college student acceptance toward SaaS-based academic information systems were examined using the Unified Theory of Acceptance and Use of Technology (UTAUT) model that was modified by adding Trust (TR) and Quality of Service (QS) variables. Data were collected from 338 college students and analyzed with Generalized Structured Component Analysis (GSCA). This study reveals that the significant predictors of SaaS-based academic information systems are performance expectancy, effort expectancy, social influence, and facilitating condition. Further results and discussions are discussed.

Keywords
Cloud Computing, Software as a Service, extended UTAUT, Academic Information System, Generalized Structured Component Analysis.

1. Introduction
Cloud computing has changed how computing resources are being used and paid. Unlike traditional Information Technology (IT) deployment models, cloud computing allows Internet-accessible IT resources by third-party cloud service providers, usually on a subscription or pay-per-use basis (Marston et al., 2011). This model allows organizations to reduce their capital investment in infrastructure but have flexible access to a large pool of resources tailored to their needs. These advantages have led many organizations to reorganize their IT strategies to include cloud computing (Oliveira et al. 2014). Universities as organizations must keep abreast of technological developments, always looking for more efficient and effective ways to develop IT-based services. The SaaS service model that uses a flexible payment scheme is a solution for universities (Sultan 2010). The academic information system is one of the higher education information systems that adopt the SaaS service model. This system is the backbone of higher education management in more than 60% of universities in Indonesia, where 80% of higher education services ranging

from new student admissions, graduation, and even campus accreditation, can be done through the academic information system (Palilingan and Batmetan, 2018).

This research was conducted at one of the public universities in Indonesia. This college has been using an on-premises- based academic information system for six years and decided to switch to a SaaS-based academic information system in 2021. Although top management support is the most influential factor in adopting Saas technology (Rahman and Pribadi Subriadi, 2022), the use of this system for students has not been maximized even though it is fully supported by management. It is proven by the number of students accessing this system, which is still fluctuating, which only increases at the beginning of the lecture period but tends to decrease in other months. Then there are still modules that have not been used since the system was implemented. At the same time, the vendor considers the implementation complete, and the management considers the system to be running well. Analyzing student acceptance of this SaaS- based academic information system is necessary based on these problems. In measuring the factors that affect technology acceptance at the user level, the UTAUT model is widely used in various studies to measure the factors that influence the adoption of cloud technology, especially from an individual perspective (Khayer et al. 2021).

This study investigates variables that affect user acceptance of a SaaS-based academic information system using the extended UTAUT model with Trust and Quality of Service. The novelty of this research lies in its object, namely the acceptance of a SaaS-based academic information system to students. This study will provide an analysis of the factors that influence technology acceptance in students so they can be considered for implementing technology in universities.

2. Research Model

A proposed conceptual model, as shown in Figure 1, is based on the UTAUT model that aims to explain user intention and adoption of a technology based on certain variables (Venkatesh et al., 2003). UTAUT consists of four main variables, namely Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC). This model also has a moderating construct consisting of Gender, Age, Experience, and Voluntariness of Use, but in this research moderating construct is not used because the use of this system is mandatory for the student. Furthermore, the dependent construct consists of Behavioral Intention (BI) and Use Behavior (UB). PE can be interpreted as measuring the degree to which an individual believes using technology can improve their work performance. EE is a measure of the ease with which individuals use technology. Easy and convenient use will increase an individual intention to use the system and vice versa. SI is a measure of the degree to which an individual perceives or believes that colleagues, family, and even other people need to participate in using technology. FC is defined as the extent to which an individual believes that the provision of organizational infrastructure and technology can support the use or acceptance of the system. BI is a variable measure that states the level of individual intention to use technology. An individual intention to use technology impacts the frequency with which a person uses the technology. Use Behavior is defined as the level of an individual behavior towards the use of technology or how often a person uses technology. These variables are related to an individual reaction and behavior totechnology, impacting the frequency of using the technology (Venkatesh et al., 2003).

As an extension to basic UTAUT, we added QS and TR variables to measure student acceptance of SaaS-based academic information systems. QS is a description or measurement of the performance of all services (Burkon, 2013; Alotaibi, 2016). QS is a significant predictor of attitudes and intentions towards different technologies. In his research on the use of mobile technology in the health sector, Akter et al. (2010) found that QS is a significant predictor of attitudes towards mobile technology. Alharthi et al. (2015) included service quality variables such as reliability and bandwidth as factors influencing intentions and behavior towards cloud-based educational services. Alotaibi (2016) also found that the higher the Quality of Service, the higher the user's intention to use SaaS, especially for private and public employees in Saudi Arabia. QS in this research will be measured with four indicators: reliability, usability, responsive, and customizable (Burkon, 2013; Alotaibi, 2016).

Trust is the accumulation of trust from technology users based on integrity, convenience, and ability that can increase user's willingness and intention to use technology (Gefen et al., 2003). In cloud computing, the service provider's reliability and trustworthiness significantly affect technology acceptance (Wang, 2011; Lian, 2015; Jaradat et al., 2020; Khayer et al., 2021). This research will measure trust with three indicators: trust in service providers, application, and security (Lian, 2015; Jaradat et al., 2020).

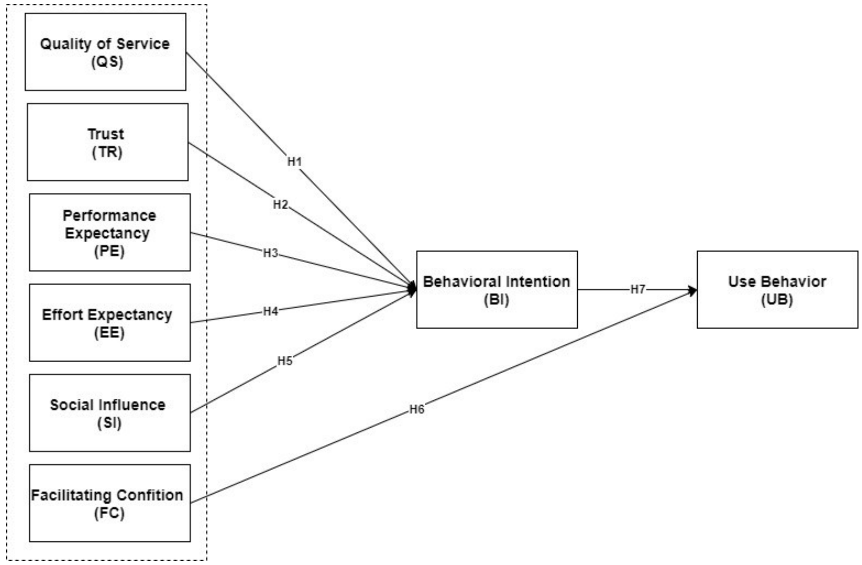

Figure 1. Proposed research model

There are seven hypotheses proposed as follows:

- H_1 : QS affects the BI significantly in the positive direction
- H_2 : TR affects the BI significantly in the positive direction
- H_3 : PE affects the BI significantly in the positive direction
- H_4 : EE affects the BI significantly in the positive direction
- H_5 : SI affects the BI significantly in the positive direction
- H_6 : FC affects the UB significantly in the positive direction
- H_7 : BI affects the UB significantly in the positive direction

3. Methods

3.1 Study Procedure and Measure

Data collection was conducted online at one public university that uses SaaS-based academic information systems in Indonesia. The respondent consists of the student from any faculty and degree. The measurement items contained twenty-one questions, as presented in Table 1. The Likert scale was used to measure the items.

Table 1 Measurement items

Construct	Measurement Item	Reference
Quality of Service (QS)	I believe this SaaS-based academic information system is responsive (QS1)	(Burkon, 2013; Alotaibi, 2016)
	I believe this SaaS-based academic information system is reliable (QS2)	
	I believe this SaaS-based academic information system can be adapted to my needs (QS3)	
	I believe this SaaS-based academic information system is worth using (QS4)	
Trust (TR)	This SaaS-based academic information system service provider can be trusted (TR1)	(Lian, 2015. Jaradat et al., 2020)
	I believe in this SaaS-based academic information system performance and feature (TR2)	
	I believe in this SaaS-based academic information system security (TR3)	
Performance Expectancy (PE)	This SaaS-based academic information system is beneficial in my daily work (PE1)	(Lian, 2015. Alotaibi, 2016. Jaradat et al., 2020)
	Using a SaaS-based academic information system speeds up the completion of my work (PE2)	

	Using a SaaS-based academic information system increase my productivity (PE3)	
Effort Expectancy (EE)	This SaaS-based academic information system is easy to learn (EE1)	(Venkatesh et al., 2003)
	This SaaS-based academic information system is easy to use (EE2)	
	Easy to become proficient in using this SaaS-based academic information system (EE3)	
Social Influence (SI)	I use this SaaS-based academic information system because people around me also use it (SI1)	(Venkatesh et al., 2003; Lian, 2015. Alotaibi, 2016; Jaradat et al., 2020)
	My close friend think I should use this SaaS-based academic information system (SI2)	
Facilitating Condition (FC)	I have the resources needed to use this SaaS-based academic information system (FC1)	(Venkatesh et al., 2003)
	I have the necessary knowledge to use this SaaS-based academic information system (FC2)	
	I get help from friends/others when I have trouble using this SaaS-based academic information system (FC3)	
Behavioral Intention (BI)	I intend to continue using this SaaS-based academic information system (BI1)	(Jaradat et al., 2020)
	I will use this SaaS-based academic information system as often as possible (BI2)	
Use Behavior (UB)	The intensity of use of this SaaS-based academic information system	(Alotaibi, 2016; Jaradat et al., 2020)

3.2 Sample

In this research, purposive sampling is used, with the respondent is a university student that already used SaaS-based academic information systems. A total of 351 respondents participated in this study. Table 2 gives the profile information of the respondents.

Table 2 Respondent Profiles

Variables		**Frequency**	**Percentage**
Usage Time	6 month – 1 year	270	77%
	>1 year	81	23%
Gender	Male	89	25%
	Female	262	75%
Age	<20	126	36%
	20 – 30	219	62%
	31 – 40	6	2%
	>40	0	0%
Education	Senior High School	286	81%
	Diploma	1	0.3%
	Bachelor	64	18%
	Postgraduate	0	0%

3.3 Analysis Technique

Generalized Structured Component Analysis (GSCA) with GSCA Pro 1.1.6 software by Hwang and Takane (2004) was used to estimate the model. The analysis of the model is carried out in three stages: testing the outer model, the inner model, and the overall model (Hwang and Takane, 2014). A 351 sample is sufficient to use in this model analysis. (Table 3)

Table 3 Convergent Validity Test

Variable	Indicator	Factor Loading	AVE	Result
Quality of Service	QS1	0.821	0.702	Valid
	QS2	0.869		Valid
	QS3	0.833		Valid
	QS4	0.828		Valid
Trust	TR1	0.874	0.754	Valid
	TR2	0.873		Valid
	TR3	0.857		Valid
Performance Expectancy	PE1	0.857	0.743	Valid
	PE2	0.875		Valid
	PE3	0.853		Valid
Effort Expectancy	EE1	0.884	0.774	Valid
	EE2	0.883		Valid
	EE3	0.873		Valid
Social Influence	SI1	0.904	0.817	Valid
	SI2	0.904		Valid
Facilitating Condition	FC1	0.856	0.739	Valid
	FC2	0.854		Valid
	FC3	0.869		Valid
Behavioral Intention	BI1	0.907	0.826	Valid
	BI2	0.912		Valid
Use Behavior	UB1	1	1	Valid

4. Results and Discussion

4.1 Measurement Model (Outer Model) Evaluation

There are two types of validity in SEM: convergent and discriminant. The convergent validity determines the validity of each relationship between the indicator and its latent construct or variable. Convergent validity means a set of indicators representing one latent variable that underlies the latent variable. This convergent validity can be assessed based on the loading factor and average variance extracted (AVE) (Ghozali 2016). An indicator can be declared to meet convergent validity if it has a loading factor value exceeding 0.70 and the AVE exceeds 0.50 (Chin and Todd 1995; Hwang and Takane 2014). Table 3 shows the result of the convergent validity test where all indicators are valid and can continue to the discriminant validity test.

The discriminant validity test aims to determine whether a reflective indicator is a good measure of its construct based on the principle that each indicator must be highly correlated only. Measures of different constructs should not be highly correlated (Ghozali, 2016). The discriminant validity test was measured by comparing square root AVE in each construct with the correlation between the constructs and other constructs in the model. In the GSCA, discriminant validity is measured by looking at the Fornell-Larcker criterion values. The discriminant validity test results are shown in Table 4. The AVE root value (bold cells) is greater than the correlation value between constructs. For example, the root value of AVE QS-QS, which is 0.838, is greater than that of TR-QS, 0.743, and so on. This mean all indicators are declared valid and can proceed to the reliability test

Table 4 Discriminant Validity Test

	QS	TR	PE	EE	SI	FC	BI	UB
QS	**0.838**							
TR	0.743	**0.868**						
PE	0.612	0.692	**0.862**					
EE	0.628	0.722	0.676	**0.880**				
SI	0.571	0.624	0.621	0.637	**0.904**			
FC	0.577	0.650	0.636	0.709	0.717	**0.860**		
BI	0.585	0.650	0.679	0.638	0.660	0.701	**0.909**	
UB	0.468	0.553	0.524	0.503	0.499	0.610	0.678	**1**

The Reliability test is used to measure the questionnaire's consistency, which is an indicator of a variable or constructs. A questionnaire is reliable if a person's answer to a question is consistent from time to time (Ghozali, 2011). The reliability test was carried out by looking at the value of Cronbach's alpha and composite reliability (Dillon-Goldstein's rho). The required value is more significant than 0.6 (Henseler et al. 2009). The reliability test results can be seen in Table 5, where all variables have Cronbach's alpha and composite reliability of more than 0.60. It can be concluded that all variables have passed a good reliability test and can be continued with the structural model test (inner model).

Table 5 Reliability Test

Variable	Cronbach Alpha	Composite Reliability (Rho)	Result
QS	0.859	0.904	Reliable
TR	0.837	0.902	Reliable
PE	0.827	0.897	Reliable
EE	0.854	0.911	Reliable
SI	0.777	0.900	Reliable
FC	0.824	0.895	Reliable
BI	0.790	0.905	Reliable
UB	1	1	Reliable

4.2 Structural Model (Inner Model) Evaluation

The inner model test tests the R-square value (coefficient of determinant), f-square value (effect size), and Path coefficient value. The R-square value assesses how much influence certain independent latent variables have on the latent dependent variable. There are three categories of grouping on the R square value, namely the strong category, moderate category, and weak category. The R-square value is categorized as strong if it is more than 0.67, moderate if it is more than 0.33 but lower than 0.67, and weak if it is more than 0.19 but lower than 0.33 (Chin 1998). The result is shown in Table 6. Variable BI and UB were moderate because they were more than 0.33 but lower than 0.67.

Table 6 R-Square Value

Variable	R-square	Result
Behavioral Intention	0.587	Moderate
Use Behavior	0.495	Moderate

The f-square value, also known as the Cohen indicator, is used to assess the magnitude of the independent variable's influence on the model's dependent variable. The f-square value of 0.02 indicates that the latent variable has a small effect, the f-square value of 0.15 indicates a moderate effect, and the f-square value of 0.35 indicates a large influence on the structural model (Cohen 1988). Table 7 shows the f-square value where the variable QS does not affect the BI.

Then the variables TR, PE, EE, and SI have a small effect on the variable BI. While the variable FC also has a small effect on the variable UB. Moreover, finally, the variable BI has a moderate influence on the dependent variable UB.

Table 7 f-square value

Variable Relation	f-square	Result
QS → BI	0.01	No effect
TR → BI	0.02	Small effect
PE → BI	0.09	Small effect
EE → BI	0.02	Small effect
SI → BI	0.08	Small effect
FC → UB	0.07	Small effect
BI → UB	0.32	Moderate effect

The path coefficient shows the direction of the relationship on the variable, whether a hypothesis has a positive or negative direction. Path coefficients have values that are in the range of -1 to 1. If the value is 0 to 1, it can be declared positive, whereas if it is in the range of -1 to 0, it can be declared negative (Ghozali 2016). The significance can be based on the estimated value of more than 0.05 and the Confidence Intervals value (95%CI). The hypothesis is declared significant if the 95%CI value range does not contain 0 (zero). Vice versa, if it contains a value of 0 (zero), it is considered insignificant. GSCA does not provide a t-test and p-value (Hwang and Choo, 2021). Based on the path coefficient value as shown in Table 8, the hypothesis that has been described can be tested based on the 95%CI value, the results of which are 7 (seven) hypotheses, Hypotheses H1, H2, and H4 are rejected, and Hypotheses H3, H5, H6, and H7 are accepted. The final model for this study is shown in Table 8.

Table 8 Path coefficient value

Hypothesized Path	Estimate	SE	95%CI	
QS → BI	0.07	0.08	-0.06	0.24
TR → BI	0.13	0.08	-0.02	0.29
PE → BI	0.28	0.07	0.14	0.44
EE → BI	0.13	0.06	-0.01	0.25
SI → BI	0.28	0.07	0.13	0.42
FC → UB	0.26	0.11	0.04	0.47
BI → UB	0.49	0.10	0.29	0.67

4.3 Overall Model Testing

The GSCA provides a measure of fit models called FIT, AFIT, and GFI. FIT is a measure that describes the variance of the data. The FIT value is between 0 (zero) to 1 (one), where the higher the FIT value, the more capable the model can explain variations from the existing data. AFIT (adjusted fit) is similar to fit but includes the degree of freedom model complexity for the null model and is the degree of freedom of the model under test and the independent parameters. The model with the largest AFIT value can be selected among the compared models. GFI (goodness-of-fit index) is the difference between the sample covariance and the covariance reproduced by the GSCA parameter estimate. The GSCA recommends the following practical limit criteria for GFI:

When the sample size is 100, a GFI of 0.89 indicates an acceptable fit. Furthermore, when the sample size is more than 100, the GFI value of 0.93 indicates an acceptable match. In this case, there is no preference for one index over another or for using a combination of indices rather than separately. Each index suggested cutoff value can be used independently to assess model fit (Ngatno, 2019; Hwang and Choo, 2021). In this research, with a sample size of more than 100, the FIT value is 0.593, which means the model can explain 59.3% variance of all variables. AFIT is 0.591, meaning 59.1% variance of all variables can be explained by the model. Furthermore, the model fit test is accepted because GFI value is 0.995 that exceed 0.93.

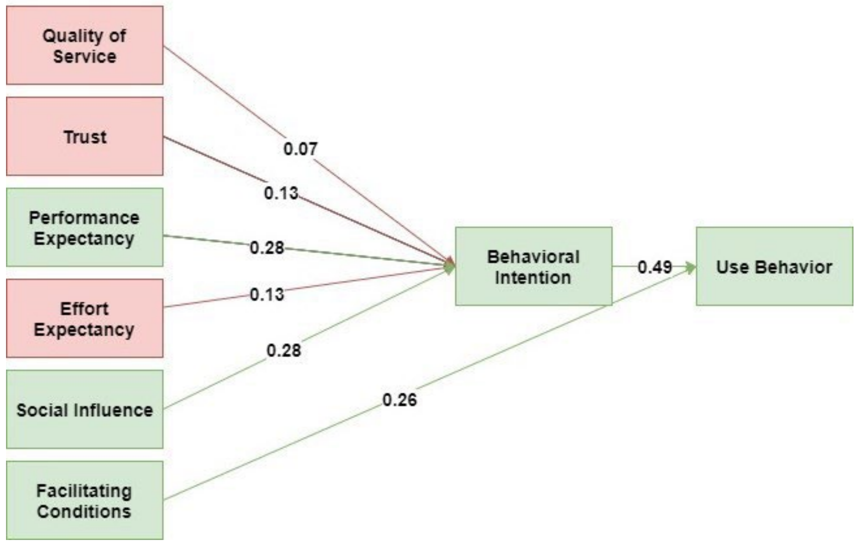

Figure 2 Final Research Model

4.3 Discussion

The model proposed examined whether: 1) Quality of Service, Trust, Performance Expectancy, Effort Expectancy, and Social Influence affect Behavioral Intention (H1, H2, H3, H4, and H5) and 2) Facilitating Condition and Behavioral Intention affect Use Behavior (H6 and H7). The estimated model found support only for H3, H5, H6, and H7. This means that students are more likely to use a SAAS-based academic information system if it is considered beneficial or helps their daily work. In addition, the influence of people, such as friends, also affects the intention to use this system. Then facilitating the conditions and behavioral intentions are also significant factors for students using academic information systems. This finding is in line with the original UTAUT, and previous studies confirming the influence of these factors on behavioral intention and use behavior.

Hypothesis testing showed there's no significant correlation between Quality of Service, Trust, and Effort Expectancy (H1, H2, H4). These findings contrast with previous research conducted by Alharthi et al. (2015) and Alotaibi (2016), which confirms that Quality of Service is a significant antecedent of SaaS Adoption. These findings also contradicted previous research by Khayer et al. (2021) which proved that Trust is a significant predictor of cloud computing adoption. In addition, this research also fails to validate that effort expectancy (H4) significantly affects Behavioral Intention positively. It's different from the original UTAUT model that proves EE significantly affects Behavioral Intention.

5. Conclusion

This research examines the factors influencing college student acceptance toward SaaS-based academic information systems with an extended UTAUT model with Trust (TR) and Quality of Service (QS). The hypothesis testing results show that only four got strong support among the seven hypotheses proposed. This research has theoretical and practical contributions. Theoretically, this research is the first to combine Quality of Service and Trust as extended factors in UTAUT model to measure the adoption of a SaaS-based academic information system in higher education. Even this factor founded not significantly affect student acceptance. Further research needs to add other factors to further determine the factors that affect student acceptance of SaaS-based academic information systems. In practical contribution, this research finding can be one of the considerations for management and vendors in implementing the system in universities. Such as the facilitating condition factor, which was very influential in increasing the use of the system by students.

Reference

Akter, S. *et al.* ‘Service quality of mHealth platforms: Development and validation of a hierarchical model using PLS’, *Electronic Markets*, 20(3–4), pp. 209–227. (2010) doi:10.1007/s12525-010-0043-x.

Alharthi, A. *et al.* ‘An overview of cloud services adoption challenges in higher education institutions’, *Proceedings of ESaaSA 2015 - 2nd International Workshop on Emerging Software as a Service and Analytics, In conjuction with the 5th International Conference on Cloud Computing and Services Science - CLOSER 2015*, (March 2017), pp. 102–109. (2015) doi:10.5220/0005529701020109.

Alotaibi, M.B. ‘Antecedents of software-as-a-service (SaaS) adoption: a structural equation model’, *International Journal of Advanced Computer Research*, 6(25), pp. 114–129. (2016) doi:10.19101/ijacr.2016.626019.

Burkon, L. ‘Quality of Service Attributes for Software as a Service’, *Journal of Systems Integration*, 4(3), pp. 38–47(2013). doi:10.20470/jsi. v4i3.166.

Chin, W.W. *The Partial Least Squares Approach to Structural Equation Modeling*.

Chin, W.W. and Todd, P.A. ‘On the use, usefulness, and ease of use of structural equation modeling in mis research: A note of caution’, *MIS Quarterly: Management Information Systems*, 19(2), pp. 237–246. (1998) doi:10.2307/249690. (1995)

Cohen, J. *Statistical Power Analysis for the Behavioral Sciences*. 2nd ed. Hillsdale, NJ: Lawrence Erlbaum Associates. (1988)

Gefen *et al.* ‘Trust and TAM in Online Shopping: An Integrated Model’, *MIS Quarterly*, 27(1), p. 51. (2003) doi:10.2307/30036519.

Ghozali, I. *Aplikasi Analisis Multivariate Dengan Program SPSS*. Semarang: Badan Penerbit Universitas Diponegoro(2011).

Ghozali, I. *Aplikasi analisis multivariete dengan program IBM SPSS 23*. edisi dela. Semarang: Badan Penerbit Universitas Diponegoro. (2016)

Henseler, J. *et al.* (‘The use of partial least squares path modeling in international marketing’, *Advances in International Marketing*, 20(May 2014), pp. 277–319. (2009) doi:10.1108/S1474-7979(2009)0000020014.

Hwang, H. and Choo, H. ‘GSCA Pro 1.1 User’s Manual’. doi:10.13140/RG.2.2.28162.61127. (2021)

Hwang, H. and Takane, Y. ‘Generalized structured component analysis’, *Psychometrika*, 69(1), pp. 81–99. (2004) doi:10.1007/BF02295841.

Hwang, H. and Takane, Y. *Generalized Structured Component Analysis*. Chapman and Hall/CRC. (2014) doi:10.1201/b17872.

Jaradat, M.R.M. *et al.* ‘Exploring Cloud Computing Adoption in Higher Educational Environment: An Extension of the UTAUT Model with Trust’, *International Journal of Advanced Science and Technology*, 29(5), pp. 8282–8306. (2020)

Khayer, A. *et al.* ‘The adoption of cloud computing in small and medium enterprises: a developing country perspective’, *VINE Journal of Information and Knowledge Management Systems*, 51(1), pp. 64–91. (2021) doi:10.1108/VJIKMS-05-2019-0064.

Lian, J.W. ‘Critical factors for cloud-based e-invoice service adoption in Taiwan: An empirical study’, *International Journal of Information Management*, 35(1), pp. 98–109. (2015) doi:10.1016/j.ijinfomgt.2014.10.005.

Marston, S. *et al.* ‘Cloud computing - The business perspective’, *Decision Support Systems*, 51(1), pp. 176– 189. (2011) doi: 10.1016/j.dss.2010.12.006.

ngatno *Analisis Data Penelitian dengan Program GeSCA*. Undip Press, Semarang. (2019)

Oliveira, T. *et al.* ‘Assessing the determinants of cloud computing adoption: An analysis of the manufacturing and services sectors’, *Information and Management*, 51(5), pp. 497–510. (2014) doi:10.1016/j.im.2014.03.006.

Palilingan, V.R. and Batmetan, J.R. ‘Incident Management in Academic Information System using ITIL Framework’, *IOP Conference Series: Materials Science and Engineering*, 306(1). (2018) doi:10.1088/1757-899X/306/1/012110.

Rahman, A. and Pribadi Subriadi, A. ‘Software as a Service (SaaS) Adoption Factors: Individual and Organizational Perspective’, *Proceedings - 2022 2nd International Conference on Information Technology and Education, ICIT and E 2022*, pp. 31–36. (2022) doi:10.1109/ICITE54466.2022.9759891.

Sultan, N. ‘Cloud computing for education: A new dawn?’, *International Journal of Information Management*, 30(2), pp. 109–116. (2010) doi: 10.1016/j.ijinfomgt.2009.09.004.

Venkatesh *et al.* ‘User Acceptance of Information Technology: Toward a Unified View’, *MIS Quarterly*, 27(3), p. 425. (2003) doi:10.2307/30036540.

Wang, Y.H. ‘The impact of credibility trust on user acceptance of software-as-a-service’, *Proceedings - 16th*

North-East Asia Symposium on Nano, Information Technology and Reliability, NASNIT 2011, pp. 11–16. (2011) doi:10.1109/NASNIT.2011.6111113.

Biographies

Abd. Rahman graduated from Sekolah Tinggi Manajemen Informatika dan Komputer (STMIK) Dipanegara with a bachelor's degree in information system in 2003. In 2020 began his master's degree in Department of Information Systems, Institut Teknologi Sepuluh Nopember, Surabaya, Indonesia. His research interest is Software as a Service (SaaS) and Technology Acceptance.

Reny Nadlifatin is an Assistant Professor at Department of Information System, Institut Teknologi Sepuluh Nopember. Dr. Nadlifatin research area is about human behavior and technology acceptance.

Satria Fadil Persada is an Assistant Professor at Entrepreneurship Department, Bina Nusantara University. Dr. Persada research area is about consumer behavior and behavioral science.