Exploring Cloud Computing Readiness and Acceptance in Higher Education Institution: A PLS-SEM Approach

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Abstract: The COVID-19 pandemic has altered nearly every aspect of life, including education. Technology has replaced face-to-face teaching and learning nearly totally. This health disaster has accelerated digitization in the world of education, which was previously only available without a repulsive factor. Cloud computing technology has been widely used in education, including higher education, enabling teaching resources, educational information, notes, lectures, and academic assessments to be accessed and shared online. Yet, in celebrating the greatness of technology, are users ready to accept an explosion of information resources and access openly online through cloud-based services? Thus, this research will investigate the Higher Education Institution (HEI) users' readiness and acceptance of cloud computing. The research employs the Technology Acceptance Model (TAM) and Technology Readiness Index (TRI) model together with Structural Equation Modeling (SEM) to investigate 470 individuals from HEIs in Malaysia. Perceived Ease of Use and Perceived Usefulness are found to be positively significant in explaining why a user decides to use cloud computing. Optimism and innovativeness have found to affect the factors of technology acceptance significantly. In contrast, discomfort and insecurity do not affect technology acceptance factors, except for insecurity that negatively impacts Perceived Usefulness. This study contributes to another finding to studying technology readiness and acceptance, especially in higher education.

Keywords: Cloud Computing, Technology Readiness, Technology Acceptance, HEI, SEM

1. Introduction

The COVID-19 pandemic situation that is sweeping the world has changed teaching and learning in almost all educational institutions. The student approach from home and online learning has been adopted as a new norm over the past year. The situation has changed the ordinary habits of human beings who previously relied on conventional methods and had to turn to technology. Despite this uncertainty, it has accelerated the adaptation of technologies in human life, such as the use of cloud computing technology.

Globally, online education has created a new pathway to higher education. Due to the closure of university and college campuses, education must now be conducted remotely and virtually. Online resources such as forums, learning portals, and YouTube have become important in online learning. To maintain learning and assessment continuity, students and instructors should be eager to embrace new technologies. According to a research by Chung et al. (2020), a moderate level of readiness are found among university students during online learning due of the pandemic circumstances they find themselves in.

Although cloud computing technology is not new, particularly in Malaysia, cloud computing applications have gained traction in the aftermath of the COVID-19 epidemic. The use of applications such as Google Classroom, OpenLearning.com, Teachable and other learning management systems (LMS) helps facilitate the learning process. Almost all of these applications make use of the cloud computing platform, which enables the sharing and collaboration of information resources, applications, and other resources. Google Cloud, for example, is a cloud computing platform that supports the teaching and learning process through the use of Google Classroom, Google Drive, Google Forms, Google Docs, and Google Sheets.

Since the COVID-19 epidemic, cloud computing has been quickly gaining popularity in universities. Students, educators and staff in HEI are all active users of cloud computing. As a result, it is necessary to determine the acceptance of cloud computing among HEI users. Therefore, this study sought (i) to understand how readiness impacts users' acceptance of cloud computing in HEI, and (ii) to study the possibility of TRI factors in raising user acceptance of cloud computing in an online setting.

2. Literature Review

2.1 Cloud computing in HEI

Challenges related to enrollment growth, the increasing need for information technology and infrastructure, the provision of high-quality education, and the affordability of educational services are encountered by the Higher education institutions (HEI) (Alexander, 2008). Due to the fast rate of information technology advancement, efficient use of resources is crucial for higher education institutions (Sultan, 2010). A flexible yet comprehensive digital transformation design incorporating diverse technologies throughout the institution, with cloud computing being a basis, is required to succeed in the new digital environment. Cloud computing has become a great solution for HEIs to assist cost reduction, quality improvement, and educational sustainability (González-Martínez & Miguel L, 2015) by offering infrastructure, software, and storage (Sultan, 2010). As a result, HEIs have increasingly adopted cloud computing (Qasem et al., 2019; Sultan, 2010), especially to manage education during the COVID-19 epidemic (Alashhab et al., 2021; Ye et al., 2020).

2.2 Technology Acceptance and Readiness Theories

Technology Acceptance Model (TAM), (Davis, 1989) proposes two attributes when studying individual acceptance of technology: Perceived Usefulness (PU) and Perceived Ease of Use (PE). PU defines "the degree to which a person believes that using technology would enhance their job performance" (Davis, 1989), while PE points out "the degree to which a person believes that using a particular system would be free from effort" (Davis, 1989). TAM is one of the earliest fundamental theories of acceptance that allows external variables to be tested together with the two factors of the theory (Hong & Yu, 2018). Besides, TAM is also suitable for predicting factors that influence technology acceptance (Sharma et al., 2016).

Technology Readiness Index (TRI) is a developed metric for determining a person's readiness to use technology (Parasuraman, 2000). TRI components are classified as drivers (optimism and innovativeness) and inhibitors (discomfort and insecurity). Optimism represents "a positive view of technology and a belief that it (technology) offers people increased control, flexibility, and efficiency in their lives" (Parasuraman & Colby, 2001), where thoughts of positivity regarding technology are measured. Innovativeness represents "a tendency to be a technology pioneer and thought leader" (Parasuraman & Colby, 2001), indicating how far ahead an organization believes itself to be in terms of implementing new technologies. Discomfort represents "a perceived lack of control over technology and a feeling of being overwhelmed by it" (Parasuraman & Colby, 2001). In general, the amount of concern and unease people have when confronted with technology is measured by this dimension. Insecurity represents "a "distrust of technology and skepticism about its ability to work properly" (Parasuraman & Colby, 2001), measuring the issues people may have while doing business with technology. Drivers (optimism and insecurity) relate to an individual's positive view of technology; these constructs are also known as contributors or motivators. In contrast, inhibitors (discomfort and insecurity) are an individual's negative view of technology that can slow down acceptance and readiness.

2.3 Past studies on Technology Readiness and Acceptance

A study by Lin et al. (2007) found that TRI has a significant effect on TAM and people's self-determining engagement in the e-service design and delivery process. Panday (2018) has investigated the relationships and effect of TRI on TAM in utilizing the university system in Jakarta. The study proved that all TRI factors have a favorable influence on Perceived Ease of Use, challenging the hypothesis, since both inhibitors factor in TRI are also positively significant. A study by Larasati et al. (2017) incorporated TRI and TAM in their study to assess SMEs' preparedness and adoption of Enterprise Resource Planning, particularly in the craft industry, to help with the implementation of strategic management planning. This study found that only Perceived Ease of Use is predicted by optimism, although prior research has shown otherwise. In comparison, innovativeness impacts Perceived Usefulness and Perceived Ease of Use.

3. Methodology

3.1 Sampling, Data Collection and Instrument Development

A convenience sampling technique was employed among cloud computing users in Higher Education Institutions, Malaysia. To determine the adequacy of the sample size, the G*Power software was implemented. Using Cohen's (1988) recommended values, the proposed PLS model requires a minimum of 85 samples to obtain a power of 0.80 when there are four predictors. Yet, the data collected are 470; thus, a power of around 0.99 was achieved with a medium effect size. Thus, the sample size acquired is greater than the required minimum.

This study adopted the online survey approach via survey monkey to collect information invalidating the proposed conceptual framework. The survey consists of four exogenous constructs consisting of TRI variables (Optimism, Innovativeness, Discomfort, and Insecurity) and three endogenous constructs (Perceived Ease of Use, Perceived Usefulness, and Use Intention) with 30 questions.

To satisfy the research objectives, a survey questionnaire was developed. Part 1 of the questionnaires includes demographic information (gender, education level, job position, geographical area, and age), whereas Part 2 comprises each construct. Questions of items for each construct in Part 2 were altered, by adapting questions based on prior research. To categorize survey items, the Likert Scale is employed, with 1 representing major disagreement and 5 indicating major agreement. Table 1 presents the survey items for each construct used in TAM, while items in TRI* (Parasuraman & Colby, 2014) are not presented.

Table 1. Survey items for each construct in TAM

Items	Questions
Perceived Usefulness (Davis, 1989; Ibrahim et al., 2017)	
PU1	Learning to interact with Cloud Computing application would be easy for me
PU2	I find the Cloud Computing application to be easy to use
PU3	It is easy to become skillful at using the Cloud Computing application
PU4	It would be easy for me to find information at the Cloud Computing application
PU5	I would find it easy to get the Cloud Computing application to do what I want to do
Perceived Ease of Use (Ibrahim et al., 2017)	
PE1	Advancing studies through Cloud Computing application can help my work/learning be more efficient

PE2	Advancing studies through using Cloud Computing application can help me acquire the information I want to acquire
PE3	Advancing studies through using Cloud Computing application can be helpful to my work or learning
PE4	Cloud Computing application would improve my work/learning performance
PE5	Cloud Computing application would increase my academic/work productivity
Use Intention (Ibrahim et al., 2017)	
UI1	I prefer Cloud Computing application to conventional installed application
UI2	I think Cloud Computing application should be implemented in a higher learning institution
UI3	I will recommend Cloud Computing application to my colleagues
UI4	I intent to use Cloud Computing application for my work/learning

*Note: * = These questions comprise the Technology Readiness Index 2.0 which is copyrighted by A. Parasuraman and Rockbridge Associates, Inc., 2014. This scale may be duplicated only with written permission from the authors.*

3.2 Model and Hypothesis Development

The TAM has been employed in past studies, making it particularly relevant in the current literature on acceptance of technology. A recent systematic review showed that TAM is effective when compared to other theoretical models in assessing technology acceptability in education (Al-Qaysi et al., 2020). When it comes to predicting the future use of technology, TAM proposes measuring an individual's intention to use technology, which is based on two variables: Perceived Usefulness and Perceived Ease of Use. Both elements are considered to influence an individual's Use Intention towards technology. In addition, Perceived Ease of Use is theorized to predict the Perceived Usefulness of the technology. Thus, the developed hypotheses in the theory of TAM in relation to the usage of cloud computing among HEI are as follow:

H1: Perceived Usefulness has a positive significant effect on Use Intention.
H2: Perceived Ease of Use has a positive significant effect on perceived Usefulness.
H3: Perceived Ease of Use has a positive significant effect on Use Intention.

In a preliminary study, external variables influence perceived usefulness and perceived ease of use. Thus, this study identified TRI as the external factors that are likely to predict the user's acceptance of cloud computing application. Previous studies have successfully incorporated TRI and TAM in the context of technology adoption (Larasati et al., 2017; Lin et al., 2007; Panday, 2018). Thus, the hypothesis developed are as follow:

H4: Optimism has a positive significant effect on Perceived Usefulness.
H5: Optimism has a positive significant effect on Perceived Ease of Use.
H6: Innovativeness has a positive significant effect on Perceived Usefulness.
H7: Innovativeness has a positive significant effect on Perceived Ease of Use.
H8: Discomfort has a positive significant effect on Perceived Usefulness.
H9: Discomfort has a positive significant effect on Perceived Ease of Use.
H10: Insecurity has a positive significant effect on Perceived Usefulness.
H11: Insecurity has a positive significant effect on Perceived Ease of Use.

4. Results and Discussion

4.1 Descriptive Statistics

A total of 470 respondents participated in this study, and the demographics information are presented in Table 2. 347 females (73.83%) accounts for most of the respondents compared to 123 males (26.17%). A total of 426 students answered the questionnaire, out of which 261 (55.53%) are diploma students, 158 (33.62%) are bachelor students, 4 (0.85%) are masters students and 3 (0.64% are

PhD students. Meanwhile, 44 staffs participated in this study, where 12 (2.55%) are from the administration department, and 32 (6.81%) are academician. Furthermore, 189 (40.21%) are from the rural area, while 281 (40.21%) are from urban area. The age of the respondents ranges from <20 years (37.23%), 20-29 years (52.77%), 30-39 years (6.6%), 40-49 years (2.13%) and 50-59 years (1.28%). Table 2 show the summary respondents of the study.

Table 2. Demographic Information

Demographic Characteristics	Items	Number of Respondents	%
Gender	Male	123	26.17
	Female	347	73.83
Education Level (Students)	Diploma	261	55.53
	Bachelor	158	33.62
	Masters	4	0.85
	PhD	3	0.64
Job Position (Staff)	Administration	12	2.55
	Academician	32	6.81
Geographical Area	Rural	189	40.21
	Urban	281	59.79
Age	<20	175	37.23
	20-29	248	52.77
	30-39	31	6.60
	40-49	10	2.13
	50-59	6	1.28

4.2 Partial Least Squares-Structural Equation Modelling (PLS-SEM)

To examine the research model, SmartPLS Software was utilized, in which two-stage analytical procedures were employed (Anderson & Gerbing, 1988). Measurement model was first studied, and then followed by the examination of the structural model (Hair et al., 2016). A single source for data collection in quantitative research can be compromised due to common method variance (CMV). CMV is the variation that results from using different measuring instruments. Therefore, prior to conducting any inferential analysis, it is critical to check the CMV (Podsakoff et al., 2003). The criterion is that the total variance explained by the first unrotated factor in unrotated factor analysis must be no greater than 40%, as Harman's single-factor test suggested. The test indicated a maximum covariance of 29.62% (with regards to common method variance), and hence was not seen as a concern to this study. Mardia's statistic was assessed to check the multivariate normality as recommended by Hair et al. (2016) using the Web Power online tool. The Mardia's multivariate skewness ($\beta = 2.798283$, $p < 0.01$) is above the threshold of +1 while Mardia's multivariate kurtosis ($\beta = 72.311914$, $p < 0.01$) above the threshold of +20. Therefore, the data collected is not multivariate normal and allows Partial Least Squares-Structural Equation Modelling (PLS-SEM) to be performed.

4.2.1 Measurement Model

The measurement model (outer model) highlights the relationship among constructs' indicators and is measured by assessing the reliability, convergent validity and discriminant validity (Hair et al., 2017). Reliability measures the internal construct consistency by means of composite reliability, CR. As seen in Table 3, reliability is ascertained as the values of CR are more than the recommended value of 0.7. Factor loadings and Average Variance Extracted (AVE) are examined to measure the convergent validity. The acceptable criterion is that factor loadings' values must be equal to or greater than 0.7, whilst AVE should be more than 0.5 (Hair et al., 2016). The result in Table 3 indicates that both measures are confirmed as both factor loadings, and AVE are above the recommended value. Meanwhile, OPT4, DISC1, DISC4, INS1 and INS2 were deleted due to low loadings.

Table 3. Construct Reliability and Convergent Validity

Construct	Item	Outer Loadings	CR	AVE
Optimism (OPT)	OPT1	0.769	0.818	0.601
	OPT2	0.822		
	OPT3	0.73		
Innovativeness (INNO)	INNO1	0.768	0.87	0.626
	INNO2	0.779		
	INNO3	0.802		
	INNO4	0.815		
Discomfort (DISC)	DISC2	0.854	0.823	0.7
	DISC3	0.819		
Insecurity (INS)	INS3	0.754	0.826	0.705
	INS4	0.917		
Perceived Ease of Use (PE)	PE1	0.857	0.936	0.747
	PE2	0.835		
	PE3	0.892		
	PE4	0.89		
	PE5	0.845		
Perceived Usefulness (PU)	PU1	0.782	0.923	0.706
	PU2	0.862		
	PU3	0.854		
	PU4	0.863		
	PU5	0.839		
Use Intention (UI)	UI1	0.756	0.91	0.718
	UI2	0.87		
	UI3	0.874		
	UI4	0.882		

The Heterotrait-Monotrait ratio (HTMT) is widely accepted as the critical criterion for determining discriminant validity (Henseler et al., 2015). As reported in Table 4, the HTMT values are less than the threshold value of 0.9, verifying the discriminant validity.

Table 4. Discriminant Validity

	OPT	INNO	DISC	INS	PU	PE	UI
OPT							
INNO	0.462						
DISC	0.151	0.102					
INS	0.125	0.075	0.371				
PU	0.576	0.504	0.191	0.214			
PE	0.583	0.408	0.182	0.136	0.774		
UI	0.523	0.471	0.179	0.162	0.699	0.785	

4.2.2 Structural Model

The structural model elucidates the relationship among latent constructs (Hair et al., 2016). Two measures were suggested to assess the structural model, namely the hypothesis testing and the coefficient of determination, R^2. To check for the significance of hypothesized relationships, PLS bootstrapping with 5000 re-samples (Hair et al., 2014) was performed. In addition, the predictive relevance, Q^2 and effect sizes, f^2 are also observed.

The hypothesis testing for the suggested research model is presented in Table 5. Eight out of eleven hypotheses are supported, while the remaining three hypotheses are rejected. As can be seen, PU is significantly positively influenced the UI (β=0.243, p<0.05), thus supporting H1. PE was seen to be significantly positive in affecting the PU (β=0.571, p<0.05) and UI (β=0.532, p<0.05), proving H2 and H3. The results also revealed that only OPT (β=0.102, p<0.05) and INNO (β=0.192, p<0.05) positively influence PU significantly, thus validating H4 and H6. On the other hand, INS (β=-0.082, p<0.05) was found to negatively influence PU, therefore supporting H10. However, DISC (β=-0.048, p>0.05) was found to have no significant influence on PU, so H8 is not supported. This finding is consistent with a research conducted by Walczuch et al. (2007) to determine the effect of technological readiness on technology acceptance, in which DISC was shown to have no significant effect on PU.

Moreover, OPT (β=0.395, p<0.05) and INNO (β=0.192, p<0.05) was found to have significant positive influence on PE, which in turn supports H5 and H7, whilst DISC (β=-0.087, p<0.05) and INS (β=-0.048, p>0.01) was found to have no significant influence on PE; hence H9 and H11 are not supported respectively. This result is in line with the findings by Godoe & Johansen (2012), where both DISC and INS were found to have no significant impact on PE in determining the adoption of new technologies. Multicollinearity are not a problem since all VIF values did not exceed 3.3 (Hair et al., 2011). Figure 1 shows the result of the structural model of the study.

Table 5. Path Coefficient and Hypothesis Testing

	Beta	SE	T Values	P Values	LL	UL	VIF	Decision
PU → UI	0.243	0.059	4.142	0	0.126	0.354	1	Supported
PE → PU	0.571	0.036	15.868	0	0.5	0.639	1.887	Supported
PE → UI	0.532	0.047	11.36	0	0.44	0.625	1.887	Supported
OPT → PU	0.102	0.04	2.511	0.012	0.024	0.18	2.194	Supported
OPT → PE	0.395	0.045	8.889	0	0.309	0.483	2.194	Supported
INNO → PU	0.192	0.036	5.339	0	0.121	0.261	2.194	Supported
INNO → PE	0.205	0.041	5.007	0	0.124	0.286	2.202	Supported
DISC → PU	-0.048	0.031	1.527	0.127	-0.107	0.014	2.194	Not supported
DISC → PE	-0.087	0.045	1.952	0.051	-0.175	0.003	2.202	Not Supported
INS → PU	-0.082	0.031	2.631	0.009	-0.144	-0.02	1.058	Supported
INS → PE	-0.056	0.041	1.389	0.165	-0.137	0.023	1.052	Not supported

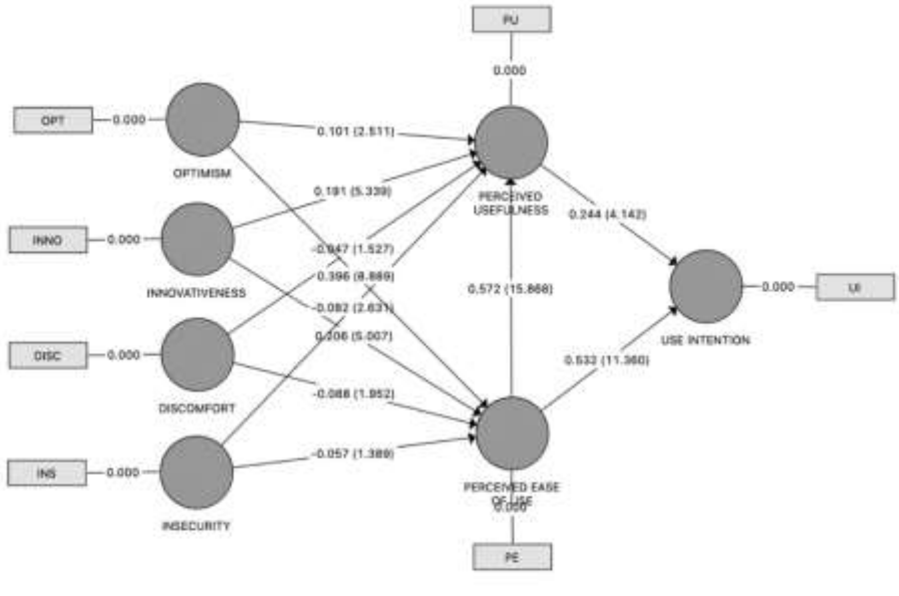

Fig. 1 Structural Model

Coefficient of determination (R^2) measures the predictive accuracy of the model. R^2 denotes the extent to which endogenous construct is verified by each external construct associated with them. According to Chin (1998), R^2 values for endogenous latent variables measured of more than 0.67 are considered high. Values between 0.33 and 0.67 are perceived as moderate, whilst values between 0.19 and 0.33 are considered weak. Table 6 shows that the predictive power of PU (R^2=0.552) and UI (R^2=0.525) can be concluded as moderate, while PE (R^2=0.152) can be considered weak. To measure the effect size, f^2, the study used the Cohen guidelines of 0.02, 0.15, and 0.35, representing the small, medium, and large effects (Cohen, 1988). As shown in Table 6, only two relationships showed medium effect size (INNO and PE, f^2 = 0.151; PE and UI, f^2 = 0.302), while the remaining are considered to have small effect size.

Additionally, Hair Jr et al. (2014) suggested establishing the predictive relevance of the model, Q2 in addition to the coefficient of determination, R^2. Q2 values of higher than zero in the structural model for a particular reflective-construct indicates that the model's path has predictive relevance required for a particular endogenous variable. As represented in Table 6, the Q2 value of 0.399 is more than zero, suggesting that the model exhibits the requisite predictive relevance.

Table 6. R^2, Q2 and f^2

Constructs	R^2	Q2	f^2		
			PU	PE	UI
OPT			0.021		
INNO			0.068	0.151	
DISC			0.004	0.02	
INS			0.015	0.007	
PU	0.552	0.258			0.063
PE	0.152	0.134			0.302
UI	0.525	0.178			

5. Conclusion

This research incorporates TAM and TRI variables to discover the theoretical relationships and contributing factors. A TRI-TAM model was developed incorporating the elements of TRI (Optimism, Innovativeness, Discomfort, Insecurity) and TAM (Perceived Usefulness, Perceived Ease of Use, Use Intention) and are evaluated using the SmartPLS software.

The result suggests that Perceived Ease of Use and Perceived Usefulness are significant predictors to Use intention. Thus, it is reasonable to state that when a student or member of staff at a higher education institution believes that cloud computing makes their job easier and that cloud computing has the potential to improve their profession, they are more likely to choose to adopt cloud computing. Moreover, the result indicated that Perceived Ease of Use is a significant predictor to Perceived Usefulness. Thus, it is demonstrated that when students and faculty of HEI see cloud computing as effortless, they are more likely to believe that cloud computing is beneficial.

The external measures used in this study are the four dimensions of TRI; Optimism, Innovativeness, Insecurity and Discomfort to predict Perceived Usefulness and Perceived Ease of Use. In general, optimism symbolizes the positive thoughts and feelings a user has about technology. At the same time, innovativeness is measured by a user's belief in the ability to be on the cutting edge of technological adoption. Whereas insecurity measures the worrisome a user may deal with when business is conducted through technology, discomfort describes fear and uneasiness a user feels while dealing with technology.

Findings revealed that not all personality dimensions of TRI influence cloud computing acceptance and usage. Optimism, innovativeness, and insecurity are the personalities that significantly affects Perceived Usefulness. Optimism and innovativeness have a positive influence on Perceived Usefulness and Perceived Ease of Use. This explains that when users who have favorable thoughts and attitudes towards the cloud computing technology and acquires believe that they are at the forefront of the technology, they may assume that it will have a favorable influence on their job performance and that the job might perhaps be easy and effortless. Meanwhile, insecurity has negative significant impact on Perceived Usefulness. This reveals that users are not concerned and worried about using cloud computing technology in business and, as a result, may conclude that it is advantageous in their line of work.

On the contrary, it is observed that the eighth hypothesis concluded that the impact of discomfort is not significant on Perceived Usefulness. In addition, in measuring Perceived Ease of Use, Discomfort and Insecurity are also found to be insignificant contributors. Apparently, users in this study are not concerned with worrisome, fear and uneasiness while dealing with cloud computing. They may have been using this technology for some time, which may explain why they are not experiencing unpleasantness.

The outcome of this study provides additional information that users in the HEI sector are confident and believe that cloud computing technology enables them to perform their responsibilities and operate more efficiently. This study also reinforces the findings of previous studies that readiness technology is an important factor that influences consumer acceptance of new technologies such as cloud computing, especially in the higher education sector in developing countries such as Malaysia.

Proposed for future studies, some external factors that have not been touched on previous studies can be integrated later. In addition, future research can test other acceptance theories such as the Unified Theory of Acceptance and Use of Technology (UTAUT) with technology readiness theory.

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7. References

Al-Qaysi, N., Mohamad-Nordin, N., & Al-Emran, M. (2020). A Systematic Review of Social Media Acceptance From the Perspective of Educational and Information Systems Theories and Models. *Journal of Educational Computing Research*, *57*(8), 2085–2109. https://doi.org/10.1177/0735633118817879

Alashhab, Z. R., Anbar, M., Singh, M. M., Leau, Y. B., Al-Sai, Z. A., & Alhayja'a, S. A. (2021). Impact of coronavirus pandemic crisis on technologies and cloud computing applications. *Journal of Electronic Science and Technology*, *19*(1), 100059. https://doi.org/10.1016/J.JNLEST.2020.100059

Alexander, B. (2008). Social networking in higher education. In *The Tower and the Cloud* (pp. 197–201).

Anderson, J. C., & Gerbing, D. W. (1988). Structural Equation Modeling in Practice: A Review and Recommended Two-Step Approach. *Psychological Bulletin*, *103*(3), 411–423. https://doi.org/10.1037/0033-2909.103.3.411

Chin, W. (1998). The partial least squares approach to structural equation modeling. *Modern Methods for Business Research*, *295*(2), 295–336.

Chung, E., Subramaniam, G., & Dass, L. C. (2020). Online learning readiness among university students in Malaysia amidst Covid-19. *Asian Journal of University Education*, *16*(2), 45–58. https://doi.org/10.24191/AJUE.V16I2.10294

Davis, F. D. (1989). Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology. *MIS Quarterly*, *13*(3), 319–340. https://doi.org/10.1016/j.cell.2017.08.036

Godoe, P., & Johansen, T. (2012). Understanding adoption of new technologies: Technology readiness and technology acceptance as an integrated concept. *Journal of European Psychology Students*, *3*(1), 38. https://doi.org/10.5334/JEPS.AQ

González-Martínez, J. A., & Miguel L, B.-L. (2015). Cloud computing and education: A state-of-the-art survey. *Computers & Education*, *80*, 132–151.

Hair, J. J. F., Hollingsworth, C. L., Randolph, A. B., & Chong, A. Y. (2017). An updated and expanded assessment of PLS-SEM in information systems research. *Industrial Management &*

Data Systems.

Hair, J. J. F., Hult, G., Ringle, C., & Sarstedt, M. (2016). *A primer on partial least squares structural equation modeling (PLS-SEM)*. Sage publications.

Hair, J. J. F., Ringle, C., & Sarstedt, M. (2011). PLS-sem: Indeed a silver bullet. *Article in The Journal of Marketing Theory and Practice*, *19*(2), 139–152. https://doi.org/10.2753/MTP1069-6679190202

Hair, J. J. F., Sarstedt, M., Hopkins, L., & Kuppelwieser, V. G. (2014). 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

Henseler, J., Ringle, C., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, *43*(1), 115–135.

Hong, S. H., & Yu, J. H. (2018). Identification of external variables for the Technology Acceptance Model(TAM) in the assessment of BIM application for mobile devices. *IOP Conference Series: Materials Science and Engineering*, *401*(1), 012027. https://doi.org/10.1088/1757-899X/401/1/012027

Ibrahim, R., Leng, N. S., Yusoff, R. C. M., Samy, G. N., Masrom, S., & Rizman, Z. I. (2017). E-Learning Acceptance Based on Technology Acceptance Mode (TAM). *Journal of Fundamental and Applied Sciences ISSN*, *9*(4S), 871–889. https://doi.org/10.4314/jfas.v9i4S.50

Larasati, N., Widyawan, & Santosa, P. I. (2017). Technology Readiness and Technology Acceptance Model in New Technology Implementation Process in Low Technology SMEs. *International Journal of Innovation, Management and Technology*, *8*(2), 113–117. https://doi.org/10.18178/ijimt.2017.8.2.713

Lin, C. H., Shih, H. Y., & Sher, P. J. (2007). Integrating technology readiness into technology acceptance: The TRAM model. *Psychology and Marketing*, *24*(7), 641–657. https://doi.org/10.1002/mar.20177

Panday, R. (2018). The Effect of Technology Readiness on Technology Acceptance in Using Services Delivery of Academic Information System. *12th Ubaya International Annual Symposium on Management*, 578–590. https://doi.org/10.31227/osf.io/8wx4y

Parasuraman, A. (2000). Technology Readiness Index (TRI): A Multipleitem Scale To Measure Readiness To Embrace New Technologies. *Journal Of Service Research*, *2*(May), 307–320. https://doi.org/10.1177/109467050024001

Parasuraman, A., & Colby, C. L. (2001). Techno-Ready Marketing: How and Why Your Customers Adopt Technology. *Journal of Consumer Marketing*, *19*(4), 359–361. https://doi.org/10.1108/jcm.2002.19.4.359.1

Parasuraman, A., & Colby, C. L. (2014). An Updated and Streamlined Technology Readiness Index: TRI 2.0. *Journal of Service Research*, 1–16. https://doi.org/10.1177/1094670514539730

Podsakoff, P. M., MacKenzie, S. B., Lee, J.-Y., & Podsakoff, N. P. (2003). Common Method Biases in Behavioral Research: A Critical Review of the Literature and Recommended Remedies. *Journal of Applied Psychology*, *88*(5), 879–903. https://doi.org/10.1037/0021-9010.88.5.879

Qasem, Y. A., Abdullah, R., & Jusoh, Y. Y. (2019). Cloud computing adoption in higher education institutions: A systematic review. *IEEE Access*, *7*, 63722–63744.

Sharma, S. K., Al-Badi, A. H., Govindaluri, S. M., & Al-Kharusi, M. H. (2016). Predicting motivators of cloud computing adoption: A developing country perspective. *Computers in Human Behavior*, *62*, 61–69. https://doi.org/https://doi.org/10.1016/j.chb.2016.03.073

Sultan, N. (2010). Cloud computing for education: A new dawn? *International Journal of Information Management*, *30*(2), 109–116.

Walczuch, R., Lemmink, J., & Streukens, S. (2007). The effect of service employees' technology readiness on technology acceptance. *Information & Management*, *44*(2), 206–215. https://doi.org/10.1016/J.IM.2006.12.005

Ye, Q., Zhou, J., & Wu, H. (2020). Using Information Technology to Manage the COVID-19 Pandemic: Development of a Technical Framework Based on Practical Experience in China. *JMIR Medical Informatics*, *8*(6), e19515. https://doi.org/10.2196/19515