Predicting the Acceptance of Cloud Computing in Higher Education Institutions by Extending the Technology Readiness Theory

Mohd Talmizie Amron[1*], Nur Hidayah Md Noh[2], Mohamad Amiruddin Mohamad[3]

[1 2]Faculty of Computer and Mathematical Sciences, Universiti Teknologi MARA,
UiTM Cawangan Terengganu, 20180 Kuala Terengganu, Terengganu, Malaysia
talmizie@uitm.edu.my
Nurhidayah0738@yahoo.com
[3]Faculty of Hotel and Tourism Management, Universiti Teknologi MARA,
UiTM Cawangan Terengganu, 23000 Dungun, Terengganu, Malaysia
amiruddinmohamad@uitm.edu.my
[*]Corresponding Author

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Abstract: The COVID-19 outbreak has impacted almost every facet of life, including education. Technology has almost entirely replaced conventional face-to-face teaching and learning environment. This public health calamity has hastened the digitisation of education, which was previously only provided without a repellent component. Cloud computing is widely used in education, notably higher education, to provide online access and share teaching resources, educational information, notes, lectures, and academic assessments. But, while observing technology's grandeur, are people prepared to accept an avalanche of information resources and open online access via cloud-based services? Thus, this study investigated users' readiness and acceptability of cloud computing in Higher Education Institutions (HEIs). Using the Structural Equation Modelling analysis, this study surveyed 470 individuals from Malaysian HEIs using the Technology Acceptance Model and Technology Readiness Index models. Perceived Ease of Use and Perceived Usefulness is positively relevant in understanding why a user chooses cloud computing. The environment of the learning process and the security factors are positive predictors of cloud computing use intention. Optimism and Innovativeness have been demonstrated to impact technology acceptance factors substantially. On the other hand, Discomfort and Insecurity do not affect technology acceptance, except for Insecurity, which negatively affects Perceived Usefulness. This research adds to the growing knowledge about technology readiness and acceptance, especially after a pandemic hits the world.

Keywords: Cloud Computing, Readiness, Acceptance, University, Higher Education, SEM

1. Introduction

Due to the global pandemic, almost all educational institutions have adjusted their teaching and learning (T&L) practices. Over the last year, the teaching approach from home and online learning has been the norm. Human beings who previously relied on conventional techniques were forced to turn to technology due to the predicament. Despite this uncertainty, technology adoption in human life has accelerated, such as the adoption of cloud computing technology.

Online education has opened up a new path to higher education worldwide. Educators and students now conduct T&L remotely and digitally due to the closing of university and college campuses. Forum platforms, learning portals, and even YouTube have become virtual online learning platforms.

Students and instructors should be eager to adopt new technology to ensure learning and assessment continuity. According to Chung et al. (2020), university students have a moderate level of preparation while online learning due to the pandemic outbreak. A similar result has been confirmed by Sim et al. (2020) where a moderate-high level of acceptance of online learning among university students.

Cloud computing is not new in developing countries like Malaysia, but cloud-based apps have become more frequently employed since the pandemic. The Learning Management System (LMS) offers a variety of facilities that provide a highly engaging and interactive cloud-based T&L experience online. Applications in the LMS are indeed very beneficial if used as best as possible. However, the exposure and readiness of users need to be given attention so that the applications offered can be used as best as possible. The findings of a study by Hamzah et al. (2021) showed that it is crucial to assess the extent to which students are willing to use technology in their learning environment to ensure the quality of T&L can achieve the goals of a course. The introduction to the new technologies must be in line with users' readiness, especially in psychology and knowledge. The failure of users to appropriately accept a technology will limit the benefits that should be enjoyed from it. Therefore, it is essential to determine users' acceptance and readiness for technology.

In this study, users in HEIs have been exposed to technology, especially during pandemics where LMS is among the T&L applications that have been widely used. Therefore, this study aims (i) to understand how readiness impacts users' acceptance of cloud computing in HEIs, and (ii) to study the possibility of technology readiness factors in raising user acceptance of cloud computing in an online setting.

2. Literature Review

2.1 Cloud computing in HEI

Higher Education Institutions (HEIs) face various challenges when faced with the conflict between efficient management and integrity in education when the COVID-19 pandemic hits the world. Constraints on movement and monitoring of learning activities have slightly reduced the quality of the T&P process, leading to non-compliance with academic rules by students and instructors (Zizka & Probst, 2022). Therefore, the adaptation of cloud computing in education has triggered increased knowledge management. This technology saves university repository costs, facilitates access to T&L processes, provides more effective academic assessment, and improves communication between students and educators (Rico-Bautista et al., 2022).

A study by Hiran (2021) to explore the socio-cultural and economic factors involved in the adoption of cloud computing in universities reveals societal beliefs, ideologies towards cloud computing, language barrier and awareness of the cloud greatly influence student acceptance in Ethiopia. The findings suggest that users' psychological readiness factors significantly impact technology acceptance. It is also in line with a study by Rajbabu (2021), who explained that university students are indeed impressed and get a significant impact from cloud computing when they understand and are aware of the benefits of the technology. Besides, Alimboyong and Bucjan (2021) discovered the impact of technology on the education system in the T&L and assessment process and communication between the university community during the pandemic. Therefore, the acceptance of technology needs to be assessed along with the user's readiness for it.

2.2 Technology Acceptance and Readiness Theories

The Technology Acceptance Model (TAM) was among the first underpinning acceptance theories that enable the exploration of independent factors and model variables (Hong & Yu, 2018). The TAM has two main variables: Perceived Usefulness (PU) and Perceived Ease of Use (PE). PU measures a person's argument that innovation helps improve their performance at work. In contrast, PE describes how a person believes that using a specific system will be simple (Davis, 1989).

The Technology Readiness Index (TRI) is a newly designed metric for measuring a person's technological readiness (Parasuraman, 2000). Drivers (Optimism and Inventiveness) and inhibitors (Discomfort and Insecurity) are two factors of TRI components. Optimism is a positive attitude toward technology and the notion that technology gives individuals more power, flexibility, and efficiency in their lives, where positive attitudes toward technology are measured. Innovativeness refers to an organisation's propensity to be a technology pioneer and thinking leader. It indicates how far ahead it believes it is in incorporating new technologies.

While Discomfort denotes a sense of being overwhelmed by technology and a perceived lack of control over it, TRI assesses people's level of anxiety and uneasiness when presented with technology in general (Parasuraman, 2000). Insecurity is a metric that measures people's concerns about technology and their doubts about its ability to function efficiently when doing business. These constructs are also known as contributors or motivators, and they relate to an individual's positive attitude toward technology. On the other hand, Inhibitors are a person's negative attitude toward technology, which might slow down adaption and readiness.

Lin et al. (2007) discovered that TRI has a considerable impact on TAM and people's self-determination in designing and delivering e-services. Panday (2018) examined the links and implications of TRI on TAM's use of Jakarta's university system. The study found that all TRI components positively impacted PE, which contradicts the prediction because both TRI inhibitors are entirely significant. Finally, Larasati et al. (2017) used TRI and TAM to assess SMEs' readiness for and adoption of Enterprise Resource Planning, particularly in the craft industry, to implement strategic management planning. Despite previous evidence, this study indicated that optimism only predicts PE. In contrast, PU and PE are influenced by innovativeness.

3. Methodology

3.1 Research Model and Hypothesis Development

The TAM has been used in previous research, making it especially important in the current literature on technological acceptance. According to a recent comprehensive review by Al-Qaysi et al. (2020), TAM outperforms other theoretical models in measuring technology acceptability in education. TAM recommends evaluating an individual's intention to use technology based on two variables: Perceived Usefulness (PU) and Perceived Ease of Use (PE). Both variables are thought to impact a person's technology use intention. Furthermore, PE is thought to indicate the technology's PU. As a result, the following hypotheses are generated:
H1: Perceived Usefulness has a significant positive effect on Use Intention.
H2: Perceived Ease of Use has a significant positive effect on Perceived Usefulness.
H3: Perceived Ease of Use has a significant positive effect on Use Intention.

Security (SEC) is a problematic factor to detach from new technologies regarding data and information. The SEC is frequently the subject of debate in cloud computing technologies, particularly when it comes to security and trust (Amron et al., 2017). This factor has significantly impacted the acceptance and adaptation to cloud computing in other previous studies (Rahi & Abd. Ghani, 2018; Zhang et al., 2018). Therefore, the study proposes:
H4: Security has positively influenced the use of cloud computing among HEIs.

The present education ecosystem encourages educators and students to embrace new technology. The present-day situation allows for a more dynamic T&L process around conventional education techniques. According to Mahesh et al. (2018), the environment significantly impacts how people accept new technologies. Nyeko & Moya (2017) also believe that the LE encourages students to accept new technology while implementing e-Learning. As a result, the research suggests that:
H5: Learning Environment has positively influenced the use of cloud computing among HEIs.

In previous studies, many external variables influence PU and PE. Thus, this study identified TRI as the external factor likely to predict users' acceptance of cloud computing applications. Furthermore, previous studies have successfully incorporated TRI and TAM in technology adoption (Larasati et al., 2017; Panday, 2018). Thus, the hypothesis developed are as follow, and the study model was shown in Fig.1:

H6: Optimism has a significant positive effect on Perceived Usefulness.
H7: Optimism has a significant positive effect on Perceived Ease of Use.
H8: Innovativeness has a significant positive effect on Perceived Usefulness.
H9: Innovativeness has a significant positive effect on Perceived Ease of Use.
H10: Discomfort has a significant negative effect on Perceived Usefulness.
H11: Discomfort has a significant negative effect on Perceived Ease of Use.
H12: Insecurity has a significant negative effect on Perceived Usefulness.
H13: Insecurity has a significant negative effect on Perceived Ease of Use.

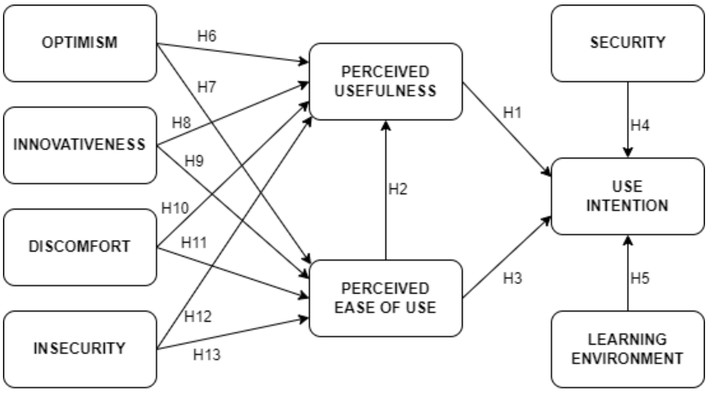

Fig. 1 Research Model

The study model containing nine variables namely Optimism, Innovativeness, Discomfort, Insecurity, Security, Learning Environment, Perceived Usefulness, Perceived Ease of Use, and Use Intention was integrated to achieve the objectives of the study.

3.2 Sampling and Research Instruments

A convenience sampling technique was employed among cloud computing users in HEIs, Malaysia. The G*Power software was used to determine the sample size's adequacy. The proposed PLS model requires a minimum of 85 samples to obtain a power of 0.80 when there are four predictors (Cohen, 1988). Yet, the data collected are 470; thus, a power of around 0.99 was achieved with a medium effect size. Therefore, 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 (OPT, INNO, DIS, and INS), three endogenous constructs (PE, PU, and Use Intention) and two other external variables (SEC and LE) with 46 questions. Table 1 presents the survey items for each construct used in TAM. However, questions in TRI are not shown due to copyright issues.

Table 1. Survey items for each construct

Items	Questions
Perceived Usefulness (Davis, 1989; Ibrahim et al., 2017)	
PU1	Learning to interact with Cloud Computing applications would be easy for me
PU2	I find the Cloud Computing application to be easy to use
PU3	It is easy to become skilful 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 applications can help my work/learning be more efficient
PE2	Advancing studies through using Cloud Computing applications can help me acquire the information I want to acquire

Items	**Questions**
PE3	Advancing studies through using Cloud Computing applications can be helpful to my work or learning
PE4	Cloud Computing applications would improve my work/learning performance
PE5	Cloud Computing applications 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 applications should be implemented in a higher learning institution
UI3	I will recommend the Cloud Computing application to my colleagues
UI4	I intend to use the Cloud Computing application for my work/learning
Security (Amron et al., 2019)	
SEC1	I believe that Cloud Computing applications are secure
SEC2	I believe that the information shared within Cloud Computing applications are under a secured communication network
SEC3	I believe that Cloud Computing application has sufficient security controls
SEC4	I believe that data in Cloud Computing applications are protected against unauthorised changes
SEC5	I believe that Cloud Computing applications always be available according to the level of user access
SEC6	I believe that Cloud Computing application is trustworthy
SEC7	I believe that Cloud Computing application is stable
Learning Environment	
LE1	Teaching and learning may require me to use Cloud Computing application
LE2	I may need to know how to use Cloud Computing applications to facilitate my teaching and learning
LE3	I will probably miss out on teaching & learning if I do not use the Cloud Computing application
LE4	People around me convinced me of the importance of using Cloud Computing application
LE5	People around me may be beneficial in assisting me in using the Cloud Computing application

To fulfil the research objectives, a survey questionnaire was developed. Questions for each construct were altered by adapting questions based on prior studies. The Likert Scale categorises survey items, with 1 representing significant disagreement and 5 indicating significant agreement.

4. Results and Discussion

4.1 Descriptive Statistics

The analysis of the study began with the demographic analysis of the respondents. Table 2 contains information on the demographics of the participants in this research with 470 participants.

A total of 347 females (73.83%) outnumber 123 males (26.17%), with 261 (55.53%) enrolled in diploma programs, 158 (33.62 %) in bachelor's programs, 4 (0.85 %) in master's programs, and 3 (0.64 %) in PhD programs. Meanwhile, 44 staff members engaged in this survey, including 12 (2.55%) from the administrative department and 32 (6.81%) from the academic department. Moreover, 189 (40.21%) are from rural areas, while 281 (40.21%) are from urban areas. The respondents are aged less than 20 (37.23 %), 20 to 29 years (52.77 %), 30 to 39 years (6.6 %), 40 to 49 years (2.13 %), and 50 to 59 years (1.28 %).

Table 2. Demographic Information

Demographic Characteristics	Items		%
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)

This study used SmartPLS software to analyse the research model, which included two-stage analytical methods; first, the measurement model was investigated initially, followed by a structural model analysis (Hair, Matthews, et al., 2017). The Common Method Variance (CMV) shows the measurement instrument's variance rather than the latent construct or measurement items themselves. This is most common when the same respondent's questionnaire is measured and answered. As a result, it is essential to check the CMV before any inferential analysis (Podsakoff et al., 2003). According to Harman's single-factor test, the total variation explained by the first unrotated component in unrotated factor analysis must be no more than 40%. The test revealed a maximum covariance of 29.62% by the common method variance and is considered satisfactory for this study.

Mardia's statistic was used to verify multivariate normality using the Web Power online application at https://tinyurl.com/webpower-analysis. Unfortunately, results showed that the data collected is not multivariate normal: Mardia's multivariate skewness ($\beta = 2.798283$, $p<0.01$) is above the +1 criterion while Mardia's multivariate kurtosis ($\beta= 72.311914$, $p<0.01$) above the +20 criterion. Therefore, PLS-SEM using SmartPLS is performed as it is a nonparametric analysis software.

4.3 Measurement Model

Two factors, reliability and validity, were examined to test the measurement model. The composite reliability (CR) is determined by conducting reliability testing, which should be more than 0.70 (Hair et al., 2017). Table 3 indicates that the CR values are acceptable, implying that their reliability is established. Two types of validity tests were conducted: convergent and discriminant to measure the validity. The factor loadings and average variance extracted (AVE) were verified against acceptable values of ≥ 0.70 and ≥ 0.50, respectively, to establish convergent validity. The findings in Table 3 indicate that both measures meet the requirements for acceptance, establishing convergent validity. However, DISC1, DISC2, INS1, and INS2 were all found to have minimal loading and so had to be removed.

Table 3. Construct Reliability and Convergent Validity

Construct	Item	Outer Loadings	CR	AVE
Optimism (OPT)	OPT1	0.702	0.82	0.533
	OPT2	0.781		
	OPT3	0.733		
	OPT4	0.702		
Innovativeness (INNO)	INNO 1	0.768	0.87	0.626
	INNO 2	0.779		
	INNO 3	0.802		
	INNO 4	0.815		
Use Intention (UI)	UI1	0.882	0.927	0.762
	UI2	0.878		
	UI3	0.876		
	UI4	0.855		
Discomfort (DISC)	DISC 2	0.854	0.823	0.700
	DISC 3	0.819		
Insecurity (INS)	INS3	0.754	0.826	0.705
	INS4	0.917		
Security (SE)	SE1	0.785	0.933	0.666
	SE2	0.856		
	SE3	0.832		
	SE4	0.822		
	SE5	0.763		
	SE6	0.851		
	SE7	0.798		
Learning Environment (LE)	LE1	0.785	0.842	0.571
	LE2	0.767		
	LE4	0.728		
	LE5	0.743		
Perceived Ease of Use (PE)	PE1	0.857	0.936	0.747
	PE2	0.834		
	PE3	0.891		
	PE4	0.89		
	PE5	0.846		
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	0.754	0.91	0.717
	UI2	0.869		
	UI3	0.875		
	UI4	0.883		

Following Henseler et al. (2015) recommendation, discriminant validity is confirmed by performing correlations' Heterotrait-Monotrait ratio (HTMT). HTMT should not exceed 0.9 to be considered acceptable to guarantee that the latent variables produced to evaluate the underlying causal relationships are different.

Table 4. Discriminant Validity

	OPT	INNO	DISC	INS	SEC	LE	PE	PU	UI
OPT									
INNO	0.508								
DISC	0.131	0.102							
INS	0.139	0.075	0.371						
SEC	0.403	0.238	0.178	0.16					
LE	0.548	0.38	0.233	0.116	0.438				
PE	0.605	0.408	0.182	0.136	0.487	0.729			
PU	0.58	0.504	0.191	0.214	0.543	0.71	0.774		
UI	0.541	0.471	0.179	0.162	0.452	0.677	0.785	0.699	

The results in Table 4 indicate that all values are acceptable, and therefore the discriminant validity is verified between two reflective constructs.

4.4 Structural Model

The structural model clarifies the relationship between latent constructs. When evaluating the structural model, two metrics were proposed: hypothesis testing and the coefficient of determination, often known as R2. 5000 re-samples were used in PLS bootstrapping to determine the significance of the predicted relationships was performed. In addition, the predictive relevance (Q2) and effect sizes (f2) are also observed.

Table 5 presents the hypothesis testing of the proposed research model. Of the thirteen possible hypotheses, ten are found to be valid, while the other three are found to be invalid. PU ($\beta = 0.178$, $p < 0.05$), PE ($\beta = 0.466$, $p < 0.05$) and LE ($\beta = 0.144$, $p < 0.05$) was determined to have a significant positive influence on UI, thus validating H1, H3 and H5. OPT ($\beta = 0.397$, $p < 0.05$) and INNO ($\beta = 0.206$, $p < 0.05$) are found to have significant positive impact on PE, supporting H7 and H9. Nonetheless, OPT ($\beta = 0.100$, $p < 0.05$), INNO ($\beta = 0.191$, $p < 0.05$) and PE ($\beta = 0.573$, $p < 0.05$) also have a significant positive influence on PU, thus supporting H6, H8 and H2. On the other hand, DISC ($\beta = -0.096$, $p < 0.05$) are discovered to have a significant negative influence on PE, and INS ($\beta = -0.083$, $p < 0.05$) are shown to have a substantial negative effect on PU, proving H11 and H12. However, DISC ($\beta = -0.046$, $p > 0.05$) and INS ($\beta = -0.056$, $p > 0.05$) was found to have no significant influence on PU and PE respectively, so H10 and H13 are not supported.

Furthermore, the results also revealed that SEC ($\beta = 0.053$, $p > 0.05$) have no significant effect on UI; hence H4 is not supported. All VIF values did not surpass 3.3; multicollinearity is not a concern (Hair et al., 2017). An abbreviated overview of the outcomes from the hypothesis testing is provided in Table 5. The structural model for this research is depicted in Fig.2.

Table 5. Path Coefficient and Hypothesis Testing

Hyp	Beta	SE	T Values	P Values	LL	UL	VIF	Decision
H1	0.178	0.064	2.764	0.006	0.049	0.303	2.314	Supported
H2	0.573	0.036	15.823	0.000	0.500	0.641	1.396	Supported
H3	0.466	0.048	9.690	0.000	0.371	0.561	2.281	Supported
H4	0.053	0.037	1.448	0.148	-0.021	0.124	1.380	Not Supported
H5	0.144	0.049	2.946	0.003	0.049	0.241	1.759	Supported
H6	0.100	0.041	2.452	0.014	0.017	0.180	1.409	Supported
H7	0.397	0.044	8.964	0.000	0.308	0.483	1.189	Supported
H8	0.190	0.036	5.271	0.000	0.117	0.260	1.239	Supported
H9	0.206	0.041	5.000	0.000	0.123	0.285	1.180	Supported
H10	-0.046	0.031	1.513	0.13	-0.107	0.015	1.077	Not Supported
H11	-0.096	0.047	2.085	0.037	-0.189	-0.006	1.064	Supported
H12	-0.083	0.032	2.632	0.009	-0.145	-0.021	1.058	Supported
H13	-0.056	0.04	1.400	0.162	-0.134	0.025	1.054	Not Supported

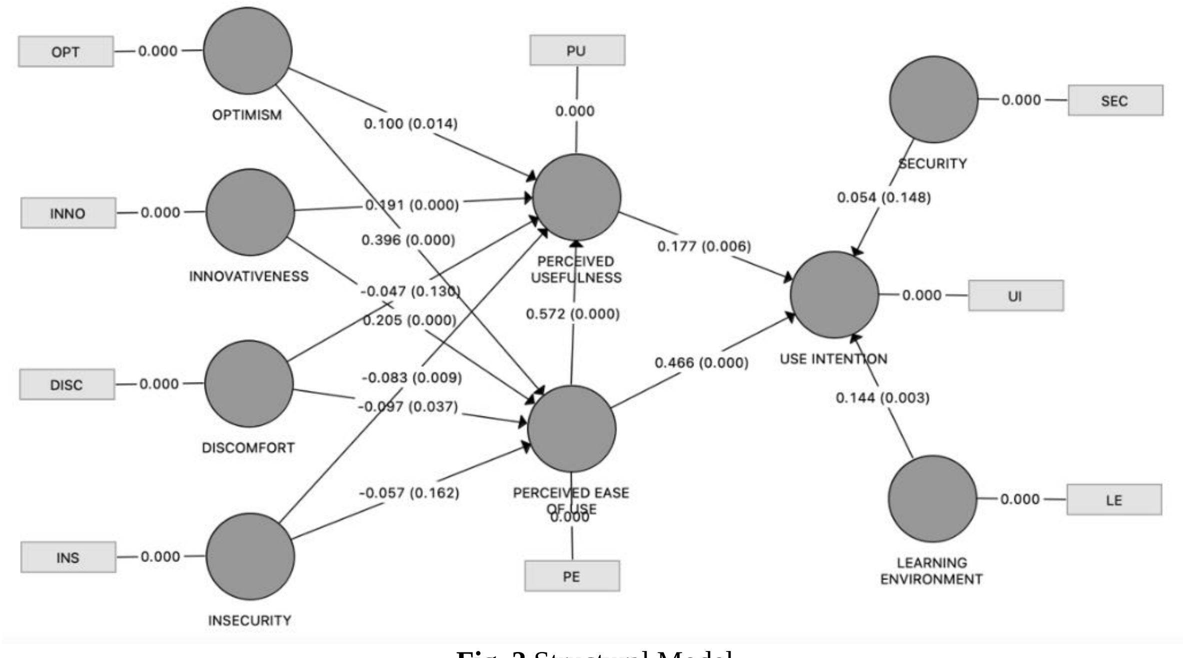

Fig. 2 Structural Model

The prediction power of the model is measured by the coefficient of determination (R2) coefficient, which indicates how much the endogenous construct correlates with each external construct associated with it. Chin (1998) defines R^2 values more than 0.67 for endogenous latent variables as 'strong' values between 0.33 and 0.67 as 'moderate' and values between 0.19 and 0.33 as 'weak'. Table 6 demonstrates that PU (R2 = 0.550) and UI (R2 = 0.539) have a moderate predictive power, whereas PE (R2 = 0.284) has a low predictive power. The recommendations of 0.02, 0.15, and 0.35 were used to determine the effect size, f2, which corresponds to small, medium, and large effects, respectively (Cohen, 1988). As in Table 6, one relationship (PE and PU, f2 = 0.521) has a large effect size, while two relationships (OPT and PE, f2 = 0.184; PE and UI, f2 = 0.207) have a medium effect size. The remaining relationships are deemed to have a small effect size.

Table 6. Coefficient of determination (R^2), effect size (f^2) and predictive relevance (Q2)

Constructs	R^2	Q2	f^2		
			PE	PU	UI
OPT			0.184	0.016	
INNO			0.05	0.065	
DISC			0.012	0.005	
INS			0.004	0.015	
SEC					0.005
LE					0.025
PE	0.284	0.265		0.521	0.207
PU	0.550	0.297			0.029
UI	0.539	0.336			

Additional recommendations by Hair et al. (2017) included determining the predictive relevance of the model, Q2, alongside the coefficient of determination, R2. For a particular reflective construct, Q2 values greater than zero in the structural model for a particular reflective construct imply that the model's path has the predictive relevance necessary for a specific endogenous variable. As shown in Table 6, the Q2 value of more than zero indicates that the model is considered valid and possesses the necessary predictive relevance.

5. Discussion

This study includes TAM and TRI variables to ascertain theoretical relationships and confounding factors. A TRI-TAM model was established and assessed using the SmartPLS software. It incorporates components of TRI and TAM. Besides, this study also demonstrates LE and SEC as possible factors that influence UI. Concerning the TAM, the findings indicate that PE and PU are essential determinants of UI. As a result, it's reasonable to assume that when a user at a higher education institution believes that cloud computing simplifies their job and has the potential to improve their profession, they'll be more likely to adopt it. This is parallel with the recent study as the author pointed out that the use of cloud computing in the context of HEIs is greatly dependent on PE and PU specifically during the COVID-19 outbreak, where cloud computing has shown the capability to facilitate the process of teaching and learning (Al-Hajri et al., 2021). Additionally, it was discovered that PE is a favourable predictor of PU. Hence, it is demonstrated that when students and staff at HEIs perceive cloud computing as easily accessible, they are more likely to feel it is beneficial.

The findings indicate that LE is a positive predictor of cloud computing use intention. The LE has gradually evolved from face-to-face learning toward blended instruction, incorporating numerous advances. Several of these initiatives incorporate technology in the form of blended learning. Furthermore, students and instructors must use distant learning due to the COVID-19 pandemic. Students, lecturers, and staff must abide by these norms, including internet technologies, one of which is cloud computing. Thus, this shows that the necessity for a learning environment in the modern-day influenced their decision to embrace cloud computing. Concurrently, the positive outcome of LE toward cloud computing can be explained due to the benefit gained by the user itself. Saad and Ehsan Rana (2019) explained that the implementation of cloud computing can enhance the LE of HEIs students by minimising the students' difficulty to access teaching and learning activities that include tools and resources.

This study also investigates SEC towards its influence using cloud computing. If users feel more secure when using cloud-based applications, they will be more willing to use and learn how to complete their duties. However, security was insignificant in predicting the use of cloud computing. Therefore, it is safe to say that how secure consumers feel when using cloud computing does not affect their use intention. Nevertheless, Le and Cao (2020) suggested that the continuous improvement of cloud technology security can increase user intention to use such technology.

Furthermore, Chen et al. (2021) reveal that despite the positive and negative four dimensions in TRI which can influence users to adopt or not towards new technology the positive and negative factors in the dimension of TRI altogether are necessary to determine the possibility of an individual to use cloud technology. Regarding the external variables, four dimensions of TRI were applied to predict PU and PE in this study and all the findings do not produce a similar outcome. The results demonstrated that not all the personality traits measured by the TRI are associated with cloud computing acceptance and usage. OPT, INNO, and INS are the personality traits that significantly impact PU. This finding indicates that individuals with high levels of OPT and INNO have higher levels of perceived usefulness. It explains that users have favourable ideas and attitudes regarding cloud computing technology, and they may expect that the technology will benefit their job performance. Meanwhile, INS has a significant negative effect on PU. This indicates that customers are confident about utilising cloud computing in the workplace and may believe it will benefit them.

Additionally, this study demonstrates that OPT, INNO, and DISC are the personality qualities that significantly influence PE. This finding proposes that optimistic and innovative individuals have higher PE. It explains that when users have favourable ideas and good attitudes about cloud computing and believe they are on the cutting edge, they may anticipate that the technology is easy to use. On the other hand, DISC has a significant negative effect on PE. This implies that individuals are neither fearful nor uneasy when confronted with technology.

It has also been discovered that DISC does not affect PU. It is reasonable to assume that users' concern when using cloud computing is insignificant in predicting its PU. They may have been using cloud computing for a significant amount of time, explaining why they are not experiencing any discomfort with its usefulness. Furthermore, INS was also found not to affect PE. The level of worry when conducting business through technology is revealed not to have any significant role in determining PE. Users may find it straightforward to use cloud computing to perform their tasks effectively, and as a result, they may not have any feelings of Insecurity.

6. Conclusion

It is the goal of this research to understand what influences Malaysia's higher education students' intention to use cloud computing services. There appears to be a strong correlation between the intention to use cloud computing with its perceived ease of use, perceived usefulness and optimism as well as the learning environment and insecurity. The findings may be beneficial for higher education institutions and cloud computing service providers to have a better grasp of the defining elements and components that should be underlined to promote and improve the usage of cloud computing among university students. Furthermore, students should be made aware of the advantages of cloud computing over traditional techniques. These capabilities are especially critical in times of crisis, such as during the COVID-19 outbreak, where cloud computing has proven to be an effective tool for global knowledge sharing while also streamlining teaching and learning processes. Moreover, the TRI-TAM model contributes significantly to behavioural theories by extending the present behavioural models, particularly that of technological adoption. These data further demonstrate the model's validity and applicability, especially those in developing countries.

7. Contribution and Suggestions for Future Research

The findings of this study contribute to another study result which shows that users from the HEIs sector think that they are confident and believe that cloud computing facilitates their tasks and work. This study also reinforces the findings of previous studies that readiness technology is an essential factor that influences users' acceptance, 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 in 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.

8. Authors' Contributions

The authors confirm their contribution to the study as follows: study conception and design: Mohd Talmizie Amron, Nur Hidayah Md Noh; data collection: all authors; analysis and interpretation of results: Mohd Talmizie Amron, Nur Hidayah Md Noh, Mohamad Amiruddin Mohamad; draft manuscript preparation: Nur Hidayah Md Noh, Mohamad Amiruddin Mohamad. All authors reviewed the results and approved the final version of the manuscript.

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