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Exploring the Factors of Using Cloud Service in Malaysia Higher Education Institutions During Covid-19 Pandemic Outbreak

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Abstract

The rapid advancement of technology has transformed higher education, with cloud educational services gaining particular significance during the Covid-19 pandemic. This study examines the factors that influence students' intention to use cloud services as part of their learning processes in Malaysian higher education institutions. To understand these factors, this study integrates constructs from two models: the Technology Acceptance Model and the Unified Theory of Acceptance and Use of Technology. The Technology Acceptance Model provides insights into perceived usefulness and perceived ease of use, while the Unified Theory of Acceptance and Use of Technology, offers insights into social influence. A quantitative survey design was employed to gather responses from 385 students from various public and private higher education institutions in Malaysia. The findings indicate that social influence, perceived ease of use, and perceived usefulness positively influence students' intention to adopt cloud learning services. Furthermore, perceived ease of use and perceived usefulness were found to mediate the relationship between social influence and cloud service adoption. The results suggest that educational institutions can enhance cloud service adoption by addressing these factors. The findings of the study highlight the need for integrating cloud services into educational practices to adapt to the evolving landscape of digital learning. Future research could include longitudinal studies, focusing on other stakeholders such as educators and policymakers, exploring post-adoption outcomes to analyse the long-term impact of cloud services in educational settings.

Keywords: cloud services, higher education, innovative pedagogy, online learning, Technology Acceptance Model, Unified Theory of Acceptance, Use of Technology

1. Introduction

During the Covid-19 pandemic, education ministries across Asian countries took proactive measures to transition from physical to online learning using online platforms such as Microsoft Teams, Google Classroom, and Zoom (Gnaneswaran, 2020). This shift has allowed millions of students to continue their learning from home while preventing the transmission of the Covid-19 virus. As a result of the pandemic, the global educational system has changed dramatically and has hastened the implementation of online teaching and learning (Mohamad, & Md Rodzi, 2021). In Asia, different countries responded to the online learning challenge in different ways. Developed nations with established e-learning frameworks adapted more smoothly, while others faced hurdles such as unreliable internet access, lack of teacher training, and digital literacy issues (Bond, 2021). In K-12 education, institutions implemented various strategies such as distributing digital devices, offering teacher training programs, and launching government-supported online learning initiatives (Bozkurt et al., 2020; Duggan et al., 2021). However, disparities persisted, particularly in rural areas with limited internet connectivity and technological access. Research on primary and secondary education highlighted the urgent need for robust digital policies and support systems to sustain e-learning. Similar challenges emerged in higher education institutions (HEIs), where students and educators struggled to adapt to fully digital classrooms.

In Malaysia, the educational learning systems at all levels have moved from physical teaching and learning practices to virtual learning (Utami et al., 2022). In implementing virtual instructional delivery, educational institutions must consider a new educational environment that embraces digital support technologies and internet infrastructure. In light of this, cloud service technology has become an ideal learning tool for the transitioning of traditional education to virtual teaching and learning. Microsoft 365 is one of the popular cloud service platforms that is widely utilized to conduct online learning in Malaysia (Kurnia & Ahmad, 2021). This software through its video conferencing tools such as Microsoft Teams, allows students and teachers to communicate digitally and exchange instructional information online (Kurnia & Ahmad, 2021). Various online learning platforms emerged during the pandemic, such as Google Meet, Zoom, Voov, DingTalk, and others. Therefore, cloud educational services have been widely used in various education systems across countries (Utami et al., 2022).

In the period of adopting the new way of learning, it is important to ensure that students can embrace the educational learning settings and technology (Atikuzzaman & Islam, 2020). Unfortunately, a significant number of students have reported the uncertainties faced when using cloud services for their learning (Utami et al., 2022). They articulated that this uncertainty was due to a lack of proper training and limited experience in using cloud services for learning. In addition, unstable network connections have worsened the use of cloud services in education as students feel frustrated and reluctant to embrace them for online learning (Atikuzzaman & Islam, 2020). The successful integration of technology into educational environments is contingent upon students' behavioural intention; otherwise, the impacts of cloud service on educational learning will be merely transient.

Deriving from the Unified Theory of Acceptance and Use of Technology (UTAUT), Dickhaut et al. (2020) postulate the need to integrate social influence (SI) as an important predictor of the intention to use cloud services. Additionally, past studies have shown that SI significantly influences the behavioral intention to use cloud services in the education system (Amron et al., 2019; Jaradat et al., 2020). However, there are some reservations regarding the relationship between SI and the adoption of cloud services, as it has been claimed that SI only affects the early phases of technological adoption and that its effect diminishes over time (Ronaghi & Forouharfar, 2020). On the other hand, previous researchers have examined the variables of the Technology Acceptance Model (TAM), such as Perceived Usefulness (PU) and Perceived Ease of Use (PEOU), in relation to the intention to use cloud computing in various workplace contexts, namely banking, retail, hospitality, and education (Dwivedi et al., 2019). However, little is known about the context of PU and PEOU of cloud services in tertiary education, particularly in Malaysia.

This study aims to bridge the existing research gap by understanding the factors that affect the intention of the higher education institution students' in using cloud services to support their application and developmental learning processes. Therefore, this study seeks to integrate and test the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) by incorporating social influence (SI) from the UTAUT model, along with perceived usefulness (PU) and perceived ease of use (PEOU) from TAM, to predict students' intention to use cloud services in tertiary education. This research will also provide preliminary and valuable insights into the impact of cloud services in influencing students' learning behaviours. Moreover, it will contribute to the understanding of how cloud services can be utilized more effectively in the educational sector; enabling HEIs to embrace cloud-based teaching and learning systems.

2. Literature Review

2.1 Technology Acceptance Model (TAM)

Developed by Fred Davis in 1989, the Technology Acceptance Model (TAM) is a conventional theory on information systems that helps to understand human behaviour regarding the acceptance or rejection of new technologies. Based on TAM, perceived usefulness and perceived ease of use are the key determinants of an individual's behaviour in accepting or rejecting a new technology. Thus, a person is more likely to accept a new technology if they find it useful and easy to use (Lina et al., 2021; Sunardi et al., 2022). While most TAM-based studies focus on general e-learning adoption they often overlook cloud-specific challenges such as security concerns, service reliability, and the need for institutional support (Atikuzzaman & Islam, 2020). Additionally, the Unified Theory of Acceptance and Use of Technology (UTAUT) model considers social influence, limited research examines how peer recommendations and institutional policies affect cloud service adoption in the Malaysian HEI context. This study aims to bridge these gaps by analyzing not only the standard TAM constructs but also the role of social influence in driving cloud platform usage.

2.2 Unified Theory of Acceptance and Use of Technology (UTAUT)

Introduced by Venkatesh et al., 2003, the Unified Theory of Acceptance and Use of Technology (UTAUT) examines technology acceptance and the factors driving its adoption. According to Almetere et al. (2020), the UTAUT is a comprehensive model with significant predictive potential regarding technology adoption intentions. The UTAUT model proposes that behavioural intention to use a technology is influenced by performance expectancy, effort expectancy, social influence, and facilitating conditions (Khechine & Augier, 2019).

While the UTAUT variables are considered determinants of a user's behavioral intention, TAM factors are based on principles of social psychology. Robles-Gómez et al. (2021) acknowledge the value of integrating UTAUT and TAM, as both are suitable for validating individual intentions to adopt new technologies. In this study, both technological and social psychological dimensions are examined using TAM and UTAUT to assess HEI students' intention to use cloud services in learning.

2.3 Intention to Use Cloud Service (INT)

Cloud services are an emerging trend in information technology systems and play an important role in education, benefitting both students and educators through the use of this technology. Cloud computing represents technological innovations in education, providing applications that enhance practices and curricula in HEIs. The Covid-19 pandemic demonstrated the critical role of cloud services in meeting the urgent demands and challenges from learning institutions, particularly for online learning (Asadi et al., 2020). Cloud-based platforms come in various classifications, including learning management systems (LMS) like Moodle and Blackboard to file-sharing services like Google Drive and OneDrive. While some studies focus on specific platforms (e.g., Google Classroom in online education), others examine broader cloud service adoption trends (Ronaghi & Forouharfar, 2020). This study expands the existing literature by addressing multiple cloud-based platforms, including LMS, collaboration tools (e.g., Microsoft Teams, Zoom), and storage solutions.

Moslehpour et al. (2018) asserted that users are willing to adopt a new cloud service technology with a learning and storage platform if they have a positive experience while using it. The effectiveness of cloud service technology could be one of the motivating factors that attract the HEI students to engage with it in their learning. According to Albashtawi and Al-Bataineh (2020), an individual's intention to use is driven by internal or self-related factors and influenced externally by their surroundings and other people. In this context, perceived usefulness (PU), perceived ease of use (PEOU), and social influence (SI) are assessed to evaluate their impact on users' acceptance of cloud service technology and its application. Therefore, this study will examine the willingness of HEI students to use cloud services in their learning process.

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2.4 Predictor Variables

In UTAUT, one of the main variables that affects intention to use technology is social influence. Social influence is defined as a person's behaviour based on their perception of what others think (Venkatesh, 2022). Furthermore, Ayaz and Yanartas (2020) suggested that social influence is when a person's behaviour is influenced by anticipating how others in a social group will view them as a result of using the technology. For the students of higher education institutions, the peers can affect their behavioural intention to adopt cloud-based learning services.

Examining university students in Lebanon, Kayali and Alaaraj (2020) highlighted the potential benefits of e-learning as well as the challenges that may hinder its adoption. Results show that social influence from peers, teachers, and family members, is significantly related to the intention to use the e-learning methods. The authors suggest that from the results, policymakers and educators can develop effective strategies to promote the use of the e-learning method.

Another study in non-pharmaceuticals intervention associated with Covid-19 virus, Haverila et al. (2022) found that social influence affects behavioural intention to use non-pharmaceuticals intervention. To curb the spread of the Covid-19 virus, communities are advised to use non-pharmaceutical interventions. As social factors may affect an individual's willingness to comply, social influence would be relevant in understanding the adoption of such measures. Purwanto and Loisa (2020) concurred that social influence drives an individual who wants to obtain conceptual identity and peer recognition status to use a system. Hence, this study proposes that:

H1: Social influence has a significant relationship with the intention of using cloud service.

Studies show that social influence has a significant relationship with perceived ease of use. In UAE, Al Kurdi et al. (2020) found that social influence positively and significantly influenced perceived ease of use which in turn influenced the behavioural intention to use the e-learning system. The study was conducted on university students to understand how they regarded and accepted e-learning system, thereby facilitating its successful adoption.

Another study in China on automated vehicle acceptance, Zhang et al., (2020) found that social influence affected perceived ease of use. It was reported that automated vehicles had not been commercialised; therefore, individuals relied on media reports and opinions from friends and family to make decisions. The effect from social influence was further amplified by the culture of collectivism and group conformity in the country (Zhang et al., 2020). In collectivist societies, social networks are effective for affecting individual perceptions on the ease of use. As such, Sathye et al. (2018) suggested that more social engagement through networks and organisations could promote rapid adoption of value-added services to the user. Therefore, this study proposes the following hypothesis:

H2: Social influence has a significant relationship with perceived ease of use.

Perceived ease of use, a construct from the Technology Acceptance Model (TAM), refers to an individual's perception of the degree of ease in using a particular system, thereby assessing the potential success of technology adoption (Sorce & Issa, 2021). The ease of use factor for cloud services technology can lead to greater acceptance by individuals (Moslehpour et al., 2018). They claim that students benefit from the convenience of accessing learning materials and class lessons, as these lessons have been recorded. This is further supported by Kayali and Alaaraj (2020), who concur that perceived ease of use is related to how easy and worry-free users find a particular technology. Their findings indicate that both perceived usefulness and perceived ease of use affect users' willingness to adopt new technologies. They explain that a lack of negative experiences and stress derived from using the technology positively influences users' behavioural intentions.

Lanlan et al. (2019) examined small businesses in China and found that perceived ease of use and perceived usefulness significantly impacted the use of computerized accounting systems. Their study aims to enhance the understanding of the relationship between acceptance and use of the system to ensure the success of the businesses. Hence, the following hypothesis is proposed:

H3: Perceived ease of use has a significant relationship with intention to use cloud service.

Several studies have also found a significant relationship between social influence and perceived usefulness. Haverila et al. (2022) found that social influence significantly impacted perceived usefulness. They postulated that the use of mass media communication could deliver information to the audience and increase awareness of the perceived usefulness of an intervention technology. In another study, Beldad and Hegner (2018) found that a descriptive social norm affected the perceived usefulness of a fitness application. The study was prompted by the popularity of fitness apps in Germany to understand users' preferences for the continuous to use of such technology. Furthermore, Izuagbe and Popoola (2017) observed that social influence affected perceived usefulness of electronic resources in Nigerian universities. Hence, this study proposes that:

H4: Social influence has a significant relationship with perceived usefulness.

Perceived usefulness is defined as the user's belief that using a new technology could improve one's performance, thus leading to the intention to use such technology (Sorce & Issa, 2021). In addition, Kayali and Alaaraj (2020) claimed that individuals are willing to use the technology not only because it is easy to use, but can improve their work efficiency too. Therefore, the perceived benefits of cloud services could serve as a stimulating factor to encourage user behaviour. Moslehpour et al. (2018) postulated that cloud services in learning are relatively more effective than traditional learning, as students can access their stored learning materials and lessons. The flexibility and usefulness allow students to learn at their discretion and revisit the content to enhance their understanding of the subject matter. Therefore, the following hypothesis is proposed:

H5: Perceived usefulness has a significant relationship with the intention of using cloud service.

Literature suggests that perceived usefulness and perceived ease of use have a mediating influence on the relationships between social influence and behavioural intention (Chen & Aklikokou, 2020; Nuryyev et al., 2020). Chen and Aklikokou (2020) found that perceived usefulness and perceived ease of use mediate the relationships between social influence and behavioural intention to use e-government services. The authors suggested that the full potential of e-government initiatives cannot be realized without sufficient adoption. Thus, the study examines the public's adoption of e-government services in Togo, a developing country, where perceived usefulness and ease of use are crucial factors. In the context of cryptocurrency payments adoption among small to medium-sized enterprises (SMEs) in the tourism and hospitality industry, Nuryyev et al. (2020) found that perceived usefulness mediates the effects of social influence on behavioural adoption intention. The study fills the gap in the limited studies and contradictory findings on IT adoption by SMEs in the tourism and hospitality industry. As a result, it offers an empirical investigation into the factors that affect the intention of tourism and hospitality SMEs to adopt cryptocurrency payments. Hence, the current study proposes the following hypothesis for the mediating roles of perceived ease of use and perceived use on the relationship between social influence and intention to use cloud services:

H6: Perceived ease of use mediates the relationship between social influence and intention to use cloud service.

H7: Perceived usefulness mediates the relationship between social influence and intention to use cloud service.

2.5 Conceptual Model

Based on the Unified Theory of Acceptance and Use of Technology (UTAUT) and the Technology Acceptance Model (TAM), the conceptual model is drawn from the constructs of Perceived Usefulness, Perceived Ease of Use, Social Influence and Intention to Use Cloud Service. Figure 1 illustrates the variables and hypothesized relationships among the variables.

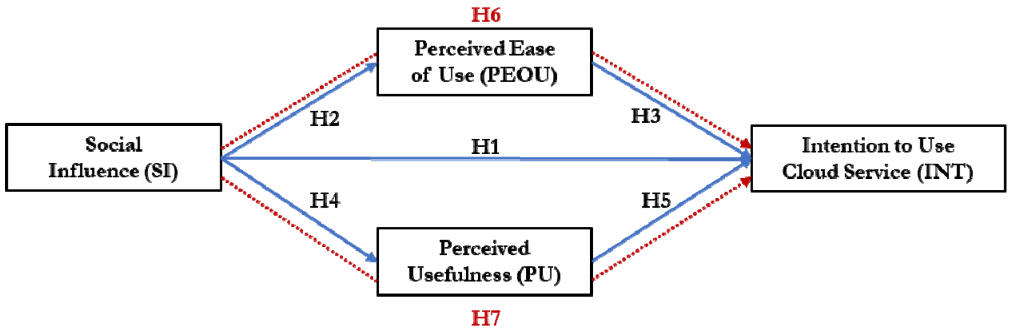

Figure 1. Conceptual Model

3. Research Method

3.1 Sample and Procedure

The target sample for the present study comprises HEI students who have the prevalence to use online learning and teaching during the pandemic in Malaysia. The target respondents are derived from public and private HEIs which consists of five universities in Malaysia, namely University of Technology Malaysia (UTM) in Johor, Universiti Tunku Abdul Rahman (UTAR) in Perak and Selangor, and Universiti Malaya (UM), Universiti Kebangsaan Malaysia (UKM), and Universiti Putra Malaysia (UPM) in Kuala Lumpur. These universities have been selected based on their inclusions in the top ten HEIs ranking in 2021. They have also been chosen because of their usage of information technologies in their institutional systems (Arumugam, 2021). In this study, the snowball sampling method has been used to distribute the questionnaires. It is an effective means of collecting large amounts of data by inviting the friends and respondents' network to be potential respondents (Parker et al., 2019). The online survey was designed to prevent respondents from submitting their replies unless they answered all the questions. A total of 450 sets of online questionnaires had been distributed, and 385 sets of questionnaires were returned, representing 85.5 percent response rate.

3.2 Measures

A survey questionnaire is used to measure all the constructs. The items in the questionnaires are extracted and modified from pre-existing measures to suit the context of cloud service (Table 1). A five-point Likert scale, ranging from 1 representing strongly disagree to 5 representing strongly agree, was employed in the questionnaire design.

Table 1. Constructs and Measurement Items

Constructs	Items	References
Perceived Usefulness (PU)	PU1: Using cloud service for study purposes suits me. PU2: Using cloud services makes my study easier. PU3: I am able to complete my work quicker because of Cloud Service. PU4: Using cloud services can improve my study performance. PU5: I find cloud services useful to my study. PU6: Using cloud services improves my study effectiveness.	Keržič et al. (2019)
Perceived Ease of Use (PEOU)	PEOU1: Using cloud services for study purposes is not difficult for me. PEOU2: It will be easy for me to find information through cloud services. PEOU3: My interaction with cloud services is understandable. PEOU4: It will be impossible to use cloud services without expert help.	Keržič et al. (2019) Venkatesh et al. (2003)

Constructs	Items	References
Perceived Ease of Use (PEOU)	PEOU5: It takes too long a time to learn to use cloud services. PEOU6: Learning using cloud services requires a lot of mental effort.	
Social Influence (SI)	SI1: I will use cloud service when my family and friends advise me to use cloud services in my studies. SI2: I will discuss the benefits of cloud services with my family and friends SI3: I will use cloud computing services because I am influenced by my family and friends. SI4: I will use cloud computing service when I realised that my family and friends around me have received benefits from using cloud services.	Cheung & Vogel (2013) Chen & Chang (2013)
Intention to Use Cloud Services	INT1: I intend to frequently use cloud services to discuss assignments or communicate with friends. INT2: I intend to use cloud services heavily. INT3: I intend to use cloud services throughout this semester and the next. INT4: I intend to repetitively use cloud services as often as possible. INT5: I believe that it is a good idea for me to use cloud services for my future coursework.	Ghani et al. (2019)

3.3 Data Analysis

This study employs Partial Least Squares Structural Equation Modeling (PLS-SEM), as it is well suited for predicting university students' intention to utilize cloud services in learning (Utami et al., 2022). Furthermore, this analytical approach is appropriate for exploring the applicability and theoretical development of UTAUT and TAM (Hair et al., 2017). The data was analyzed using SmartPLS Version 3.3.9 software.

4. Results

4.1. Descriptive Analysis

The study comprises 385 students from 5 HEIs, with 53.2% male and 46.8% female participants. The results indicate that most of the students (77.1%) are aged between 21 and 23, followed by those aged 24 and above, with the fewest being between 18 and 20 years old. The majority hold a Bachelor's degree (81.6%), while others have a Foundation certificate (3.1%), Diploma (2.9%), or Master's degree (12.5%). The findings also show that 197 students (51.2%) have been using cloud services for 2 to 3 years, 165 students (42.9%) for more than 3 years, 22 students (5.7%) from 1 to 2 years, and 1 student (0.3%) for less than a year. Additionally, students are reported to spend time on cloud services for 11 hours or more per day (30.1%), 6 to 10 hours (45.7%), 1 to 5 hours (22.3%), with 7 students spending less than an hour per day. Overall, the majority of HEI students find cloud services helpful, with some are unsure of the helpfulness of cloud service to their studies. The details of the descriptive analysis are illustrated in Table 2.

Table 2. Demographics Profile of Respondents

Demographic	Frequency n=385)	Percentage (%)
Gender:		
Male	205	53.2
Female	180	46.8
Age:		
18 to 20	25	6.5
21 to 23	297	77.1
24 and above	63	16.4
University:		
University of Malaya	33	8.6
University Putra Malaysia	38	9.9
University of Technology Malaysia	47	12.2
Universiti Kebangsaan Malaysia	50	13
Universiti Tunku Abdul Rahman	213	55.3
Others	4	1
Current Education Qualification:		
Foundation	12	3.1
Diploma	11	2.9
Bachelor's Degree	314	81.6
Master's Degree	48	12.5
How long have you been using cloud service?		
Less than 1 years	1	0.3
1 to 2 years	22	5.7
2 to 3 years	197	51.2
3 years and above	165	42.9
How long you spend on cloud service a day:		
Less than 1 hour	7	1.8
1 to 5 hours	86	22.3
6 to 10 hours	176	45.7
11 hours and above	116	30.1
Cloud service is helpful:		
Yes	372	96.6
No	0	0
Maybe	13	3.4

4.2. Assessment of Measurement Model

The study needs to fulfill the measurement and structural model assessment before PLS-SEM analysis is performed. First, the measurement model assesses the relationship between each latent variable and its items. The initial step in measuring the reflective measurement model is to test the reliability and validity of all constructs. Composite reliability analysis provides the reliability of the constructs with a threshold value of 0.70 (Hair et al., 2014). All constructs are reported to have a threshold value of 0.70 and above with composite reliability values ranging from 0.902 to 0.944. Next, the convergent validity of constructs is measured using Average Variance Extracted (AVE). AVE summarizes the indicator loadings of each construct with a rule of thumb that AVE should be above 0.5, indicating that more than half of the construct is adequately converged (Hair et al., 2017). It is reported that the AVE of all the constructs range from 0.605 to 0.772, meeting the minimum threshold of 0.5. The outer loadings for the indicators must meet the minimum value of 0.708 (Hair et al., 2014). However, the outer loading for PEOU 4 was 0.678 which is below the recommended threshold value, but this indicator was retained as the AVE and CR were deemed adequate (Ramayah et al., 2018). Table 3 depicts the assessment of reliability and validity.

Table 3. The assessment of reliability and validity

Constructs	Items	Loadings	CR	AVE	VIF
Intention to Use Cloud Services (INT)	INT1	0.895	0.944	0.772	3.424
	INT2	0.863			2.752
	INT3	0.872			2.922
	INT4	0.866			2.893
	INT5	0.897			3.344
Perceived Ease of Use (PEOU)	PEOU1	0.843	0.902	0.605	2.283
	PEOU2	0.782			1.832
	PEOU3	0.811			2.104
	PEOU4	0.678			1.597
	PEOU5	0.76			1.862
	PEOU6	0.783			2.029
Perceived Usefulness (PU)	PU1	0.891	0.935	0.706	3.322
	PU2	0.853			2.792
	PU3	0.819			2.46
	PU4	0.817			2.192
	PU5	0.816			2.272
	PU6	0.843			2.654
Social Influence (SI)	SI1	0.874	0.907	0.709	2.287
	SI2	0.818			1.922
	SI3	0.801			1.96
	SI4	0.874			2.459

Note. SI= Social Influence; PEOU= Perceived Ease of Use; PU= Perceived Usefulness; INT= Intention to use Cloud Services; CR= Composite Reliability; AVE= Average Variance Extracted; VIF= Variance Inflation Factor

Next, this study uses heterotrait-monotrait ratio of correlations (HTMT) for the assessment of discriminant validity. The HTMT value was found to be greater than 0.90 given that the HTMT value is adequate if the value is lesser than 1 (Henseler et al., 2015). Thus, the HTMT inference between the two factors is smaller than 1 (as shown in Table 4).

Table 4. The assessment of the heterotrait-monotrait ratio of correlations (HTMT)

	INT	PEOU	PU	SI
Intention to Use Cloud Services (INT)	-	-	-	-
Perceived Ease of Use (PEOU)	0.919	-	-	-
Perceived Usefulness (PU)	0.951	0.927	-	-
Social Influence (SI)	0.947	0.957	0.954	-

4.3 Assessment of Structural Model

The structural model assessment evaluates the relationship among the latent variables consisting of (1) collinearity assessment; (2) assessment of the significance and relevance of path coefficient model (3) explanatory power assessment; and (4) predictive power assessment.

4.3.1 Collinearity Assessment

After the assessment of the validity and reliability, the next assessment is the structural model in testing the relationship of the path coefficients. First, the variance inflation factor (VIF) was checked to ensure that there was no multicollinearity issue prior to the structural model assessment. The VIF values for this model are all below 3.3 (below the threshold value of 5) (shown in Table 3) (Hair et al., 2014).

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4.3.2 Assessment of the Significance and Relevance of Path Coefficient Model

4.3.2.1 Direct Effects

Next, the bootstrapping approach was used to measure the structural model with 10,000 subsamples. Table 5 presents the results of direct and indirect effects of path coefficients among the constructs. The statistical results indicate the direct effects from H1 to H5. Results of H1 stated that SI had a significant relationship with INT ($\beta = 0.258$; $p < 0.01$). H2 also mentioned that SI had significant impact on PEOU ($\beta = 0.847$; $p < 0.01$). The results for H3 indicated that PEOU had a significant impact on INT ($\beta = 0.222$, $p < 0.01$). H4 developed the fact that SI had a significant relationship with PU ($\beta = 0.853$; $p < 0.01$). H5 established the fact that PU had a significant relationship with INT ($\beta = 0.451$; $p < 0.01$).

4.3.2.2 Indirect Effects: Mediation Analysis

The indirect effects of variables are examined as H6 and H7 in this study. VAF (Variance Accounted For) technique is used to determine the strength of mediation effects by computing the ratio of the indirect-to-total effect. H6 was supported since the statistical results showed that PEOU mediated the relationship between SI and INT ($\beta = 0.188$; $p < 0.01$). The VAF value is calculated by dividing the indirect effect of 0.188 with the total effect of 0.446, resulting in 0.4215 (42.15 percent), which fell between the threshold of 20 percent and 80 percent. The findings supported H6 stating that PEOU partially mediated the relationship between SI and INT. Likewise, H7 mentioned that PU mediated the relationship between SI and INT ($\beta = 0.384$, $p < 0.01$). The VAF value was calculated by dividing the indirect effect of 0.384 with the total effect of 0.642, resulting in 0.5981 (59.81 percent). Thus, the finding supported H7 which explained that PU partially mediated the relationship between SI and INT.

Table 5. Path Coefficient Assessment

Path	Path Coefficient		Standard Deviation	Total Effect	VAF	T-values	P-values	Decision
	Direct Effect	Indirect Effect						
SI -> INT (H1)	0.258		0.063			4.062	0.00	Supported
SI-> PEOU (H2)	0.847		0.020			42.312	0.00	Supported
PEOU-> INT (H3)	0.222		0.056			3.948	0.00	Supported
SI-> PU (H4)	0.853		0.023			37.243	0.00	Supported
PU-> INT (H5)	0.451		0.062			7.217	0.00	Supported
SI->PEOU-> INT (H6)		0.188	0.048	0.446	42.15	3.885	0.00	Supported
SI-> PU -> INT (H7)		0.384	0.058	0.642	59.81	6.638	0.00	Supported

Note: SI, Social Influence; PEOU, Perceived Ease of Use; PU, Perceived Usefulness; INT, Intention to use Cloud Services; *P < 0.01

4.3.3 Explanatory Power of Structural Model

The coefficient of determination (R^2) is the analysis of regression output value interpreted as the proportion of variation in endogenous variables that may be predicted by the exogenous variable (Cohen, 2013). It assesses the prediction accuracy of the model. As suggested by Hair et al. (2017), R^2 ranging from 0.75 is regarded as substantial, 0.50 as moderate, and 0.25 is considered weak. Table 6 reveals the R^2 results of INT (0.823, substantial), PEOU (0.717, moderate) and PU (0.728, moderate).

The effect size, or f^2, is a statistical term that measures the strength of a predictor construct's link to an independent variable (Cohen, 1988). In other words, f^2 evaluates the impact of exogenous constructions on endogenous constructs. When an exogenous construct is removed from the model, f^2 investigates the change in R^2 value. According to Hair et al. (2019), an f^2 value of 0.02 indicates a little influence, a value of 0.15 indicates a medium effect, and a value of 0.35 indicates a significant effect. The results in Table 6 showed that SI (0.088), PEOU (0.067) and PU (0.258) gained the medium effects in producing R^2 for INT. In addition, SI obtained the largest effect in producing PU (2.673) and PEOU (2.563).

In PLS-SEM, the blindfolding process was used to get the Stone and Geisser's Q^2 data to report the predictive relevance of the model (Hair et al., 2019). When Q^2 values were greater than 0, the result showed that the model's predictive relevance had been established. According to Hair et al. (2019), a Q^2 value of 0.02 indicates a modest predictive relevance, a value of 0.15 indicates a medium predictive relevance, and a value of 0.35 indicates a big predictive relevance. Table 6 concluded that INT, PEOU and PU achieved the large predictive relevance as all the values were larger than 0.35 respectively.

Table 6. Explanatory Power of Structural Model

Predictor	Outcome	R^2	Consideration	f^2	Effect Size	Q^2	Predictive Relevance
SI	INT	0.832	Substantial	0.088	Medium	0.626	Large
PEOU				0.067	Medium		
PU				0.258	Medium		
SI	PEOU	0.717	Moderate	2.536	Large	0.416	Large
SI	PU	0.728	Moderate	2.673	Large	0.506	Large

Note. SI, Social Influence; PEOU, Perceived Ease of Use; PU, Perceived Usefulness; INT, Intention to use Cloud Services

4.3.4 Predictive Power Assessment

Shmueli et al. (2016) proposed PLS predict, an out-of-sample prediction approach to examine the ability of the model to forecast new or future observations. Table 7 shows that the Q^2 predict values of the model's endogenous variables (i.e. PEOU, PU, and INT) were greater than zero, with the lowest value of 0.233 and the highest value of 0.639. Following that, the root-mean square error (RMSE) values of PLS-SEM analysis were then compared with the linear regression model (LM) values for each indicator of the endogenous constructs of this model (Hair, 2020). The results indicated that the majority of the indicators in the PLS-SEM analysis had lower RMSE values compared to the RMSE values in the LM analysis. Thus, this model has achieved a medium predictive power.

Table 7. Predictive Power

INDICATORS	Q^2predict	PLS-SEM		LM		PLS- LM
		RMSE	MAE	RMSE	MAE	RMSE
INT1	0.62	0.342	0.236	0.325	0.195	0.017
INT2	0.493	0.392	0.261	0.398	0.271	-0.006
INT3	0.515	0.393	0.251	0.382	0.238	0.011
INT4	0.538	0.358	0.251	0.36	0.251	-0.002
INT5	0.616	0.329	0.229	0.331	0.218	-0.002
PEOU1	0.639	0.322	0.228	0.321	0.199	0.001
PEOU2	0.483	0.381	0.285	0.375	0.262	0.006
PEOU3	0.515	0.359	0.265	0.363	0.255	-0.004
PEOU4	0.233	0.548	0.358	0.553	0.357	-0.005
PEOU5	0.33	0.472	0.323	0.474	0.321	-0.002
PEOU6	0.33	0.501	0.313	0.496	0.331	0.005
PU1	0.615	0.345	0.221	0.336	0.192	0.009
PU2	0.462	0.397	0.269	0.389	0.272	0.008
PU3	0.498	0.384	0.267	0.386	0.259	-0.002

INDICATORS	Q^2predict	PLS-SEM		LM		PLS- LM
		RMSE	MAE	RMSE	MAE	RMSE
PU4	0.485	0.399	0.264	0.404	0.265	-0.005
PU5	0.465	0.387	0.279	0.388	0.282	-0.001
PU6	0.536	0.371	0.247	0.378	0.246	-0.007

Note. PEOU, Perceived Ease of Use; PU, Perceived Usefulness; INT, Intention to use Cloud Services

5. Discussion

5.1 Main Findings

The aim of this study is to integrate TAM and UTAUT models to predict students' intention to use cloud services at the tertiary education level. The underlying theory postulates on how social influence demonstrates the perception of the usefulness and ease of use of the cloud services and thus enabling a successful behavioural intention. Similarly, it is also articulated that individuals and groups affected students' intention in using cloud services in the early phases of technological adoption as supported by Alharbi (2017).

First, the findings depict that social influence positively affects students' intention in using cloud services, which is consistent with the results of Ayaz and Yanartas (2020) and Venkatesh (2022). This further explains that students' intention to use cloud services depends on the people around them, who influence their behaviour to act. Second, social influence is found to have a positive and significant impact on perceived ease of use, as students are influenced by their peers, friends, and community regarding the simplicity and compatibility of using cloud services. This is reflected in the students' understanding of the accessibility and adaptability of cloud services, which they can use without the help of an expert. This finding is consistent with the work of Al Kurdi et al. (2020) and Zhang et al. (2020). Third, the results indicate that perceived ease of use affects students' intention to use cloud services. This implies that when cloud service is perceived as being easy to use, the students are more likely to have the intention to use it. Simple and easy-to-understand operations are more attractive to students, helping them complete tasks quickly and efficiently. This finding is in line with the studies conducted by Source and Issa (2021) and Lanlan et al. (2019). Fourthly, this study depicts a significant relationship between social influence and perceived usefulness. This suggests that people around the students share positive thoughts and advice about the benefits of using cloud services. The finding is similar to the work of Beldad and Hegner (2018) and Harverila et al. (2022). Additionally, perceived usefulness is found to significantly influence students' behavioural intentions This relationship is consistent with the studies conducted by Moslehpour et al. (2018) and Source and Issa (2021). This relationship further suggests that when cloud services are perceived as useful, students are more likely to adopt them. For example, the usefulness of the cloud service such as the functions and features can help students improve their academic performance and complete their work more effectively.

The mediation effect of perceived ease of use between social influence and students' intention was tested and found to be significant. The empirical results reveal that perceived ease of use exerts a positive influence on both social influence and behavioral intention (Chen & Akilikokou, 2020). This implies that the ease of using cloud services can be influenced by social communities such as family and friends, thus increasing the likelihood of using the cloud service. This relationship was found to be a complementary mediation, with perceived ease of use mediating between social influence and students' intention based on the positive significance level. Lastly, the results also indicate that perceived usefulness mediates the relationship between social influence and students' intention to use cloud services. This suggests that the use of cloud services is spreading rapidly among the community, enhancing the students' judgment of practicality and suitability of the cloud service which in turn leads to the intention to use it. Perceived usefulness bridges the relationship between social influence and student's intention and this relationship further supports a complementary mediation.

The overall findings show moderate to substantial explanatory power such as perceived ease of use (0.717), perceived usefulness (0.728), and intention (0.823). This implies that 71.7% and 72.8% of the variance in perceived ease of use and perceived usefulness, respectively can be explained by social influence, while 82.3% of the variance in intention can be explained by social influence, perceived ease of use, and perceived usefulness.

5.2 Theoretical implications

This study examines the intention to adopt cloud services among university students in Malaysia using the UTAUT and TAM models, which are commonly used for examining technology acceptance. Constructs from the TAM and UTAUT include perceived usefulness, perceived ease of use and social influence on the intention to use cloud service.

Findings show that the constructs of perceived usefulness and perceived ease of use have significant relationship with intention, and that these findings align with previous research on technology adoption (Moslehpur et al., 2018, and Sorce & Issa, 2021). In this study, the perceived benefits and advantages brought by cloud services are considered a perceived usefulness, while perceived ease of use reflects a user's belief that using cloud service is effortless.

Regarding social influence, our findings show that the variable influences intention, and it is also reflected in a study by Zhang et al., (2020) which examined the acceptance of new technology in the absence of first-hand usage experience. Additionally, our findings reveal that perceived usefulness and perceived ease of use have both direct and indirect influence on the intention to use a technology-based service. Such findings are similar to those of Chen and Aklikokou (2020) which also showed that perceived usefulness and perceived ease of use mediated the relationship between social influence and behavioural intention.

Our study demonstrates the relevance of the TAM and UTAUT models in explaining the acceptance of cloud service in the context of education. Cloud service is one of many technological innovations that has surfaced in recent years. As more applications and services are developed and introduced, researchers may find it useful to incorporate the constructs of perceived usefulness and perceived ease of use, and social influence when examining intention to accept these technological innovations, especially in the field of education.

5.3 Practical Implications

This study provides insights to practitioners on the importance of social influence in the overall behavioural intention to adopt cloud-based services. The presence of social influence indicates how individuals respond to the social world where social influence leads to an increase in students' intentions. Furthermore, this suggests that social influence, to a certain extent, should be a focal point within an HEI to improve the performance and establish a positive image of its cloud services in the minds of the social group.

The findings of this study show that social influence has the largest impact on perceived ease of use and perceived usefulness. When individuals are exposed to positive value and ease of use of cloud services from their social group, they tend to react positively and are more likely to use the platform. This study does not only presents empirical results that demonstrate how a highly influential social group can lead to successful student intentions in using cloud services but also highlights how higher education institutions (HEIs) can be shaped to enhance the perceived usefulness and usability of cloud-based tasks. This ensures that tasks are performed safely, effectively, and efficiently while allowing students to enjoy the experience of the services.

This study also demonstrates how perceived usefulness is vital in enhancing students' intention in using cloud services. When students believe that cloud services will help them to achieve their goals and performance (i.e., study purposes, study effectiveness, task completion), it will then enhance their readiness to use the cloud services. Specifically, it indicates the role of the organization in developing a useful cloud service. This is to increase the likelihood of the students using the services and thus they are more likely to have the intention to use it. Therefore, the organization should not overlook the impact of perceived usefulness in developing or improving the performance of the cloud services in their planning per se activity. Similarly, students are more likely to have the intention to use cloud services when the services are perceived as easy to use. When cloud services are understandable and take less effort in learning while using, it increases the positive learning experience, and they may intend to use the platform regularly. Thus, perceived ease of use leads to the intention of students in using the services.

On the other hand, social group influence impacts students' perceived usefulness as well as their intention to use cloud services. It is important to note that social influence, such as internal and external factors, including surroundings and other individuals, influences students' decision to adopt the use of cloud services. Organizational management plays an essential role in understanding how social groups influence the willingness of university students to use cloud services through their perception of ease. Overall, the findings highlight the importance to both the educational industry and organizations to provide an updated user experience to improve the performance of cloud services. Specifically, understanding students' expectations of cloud services is pivotal for both industries in improving user comprehension of cloud service applications. This can be achieved through different methods such as helpdesks, encouraging participation from students and lecturers, and training programs to maximize the capabilities of the cloud services. In this context, it is believed that social influence is more likely to influence students' intention to use cloud services when these services are perceived as beneficial and easy to use.

6. Conclusion

This study has some shortcomings which could be addressed in future research. First, data for the current study were gathered from a sample of students from Malaysian higher institutions who utilised cloud services in their studies. Therefore, future research can be conducted in other countries to validate the findings of the current study. Second, this study model was evaluated using a one-time cross-sectional dataset. Hence, further investigation is needed to validate the TAM-UTAUT model by applying longitudinal data. Third, this study focused on student adoption of cloud services in higher education; future research could focus on academicians, government, and other authorities who use cloud services in different sectors. Fourth, this study only assessed university students' intention to use cloud service during the pandemic outbreak; future research should explore the post-adoption phase to verify the effectiveness of using cloud service in academic settings. It is also recommended that future studies examine the utilisation of cloud services in the education industry from a qualitative standpoint utilizing interviews or focus group discussions. Additionally, conducting mix-method studies by comparing the results from these two methodologies would be beneficial. Finally, the model of this study only achieves medium predictive power. Hence, future researchers can add other variables such as psychological aspects that may contribute to cloud service adoption. Other mediators or moderators such as learner involvement, information quality, and social interaction may be included in the existing model to assess their impact on cloud service adoption. Future researchers are suggested to make comparisons with student academic performance before and after using cloud service to evaluate the usefulness of cloud service in their academic achievement.

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