Moderating Effect of Technology Readiness Towards Open and Distance Learning (ODL) Technology Acceptance During COVID-19 Pandemic

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Abstract: The COVID-19 pandemic has impacted higher education in Malaysia that requires the academics to transform their teaching style to online teaching. Hence, it is essential for them to be skilful in using new technology in teaching and learning. In Open and Distance Learning (ODL), the academic staff must learn a new environment of learning technology in terms of giving lectures and managing all related ODL documents. In this perspective, technology readiness of the ODL technology plays an important role to enhance the acceptance of using the latest technology in ODL among them. This study was conducted to test the moderating effect of the Technology Readiness of the academic staff towards their acceptance of ODL technology to manage teaching and learning process such as UFUTURE and Google Classrooms. The research model was developed based on Technology Acceptance Model (TAM) and Technology Readiness concept. The online survey was created and then emailed to the academic staff in UiTM Selangor, resulting in 321 responses were received subsequently. The results show that the Technology Readiness factors (Optimism and Innovativeness) strengthen the relationship between Technology Acceptance factors (Perceived Ease of Use and Perceived Usefulness) and intention behaviour to use the ODL technology. Additionally, the direct effect testing has also shown that the related factors influence the intention of the academic staff to use the ODL technology except Insecurity and Discomfort. Technology readiness does play an important role; therefore, it is essential for the university to train academic staff on new ODL technology and it should be planned accordingly.

Keywords: Technology Readiness, Technology Acceptance, Open Distance Learning, ODL, Online Learning Platform, Education Online Tools

1. Introduction

Distance learning has a long history in Malaysia, tracing its beginning to the first offering of correspondence courses by Stamford College in the 1950s. In 1993, the Ministry of Education, Malaysia embarked on a policy encouraging universities, which included UiTM, to offer programs via distance learning. Over time, the congruence of distance and open learning, though not mutually exclusive, has often been interchangeable in practice that led to the current practice of addressing the two subjects together, namely Open and Distance Learning (ODL). Nowadays, higher education has evolved tremendously over the years in all facets. Having been influenced and shaped by numerous variables, especially due to the presence of the COVID-19 pandemic which has spread around the world since its conception, changes in higher education has come as a no surprise, hence it will only continue to grow with society (Kin et al., 2022). With the progression and improvement of technology, higher education has become accessible to millions of individuals around the world. The availability and flexibility of online learning has been one of the biggest influences shaping the digital transformation of higher education (Kentnor, 2015). In particular, during the COVID-19 pandemic, more institutions are viewing online learning as a key ingredient to strengthen the education strategy of their institution (Aguilera-Hermida, 2020).

With the development of educational technology, ODL, distance learners are required to engage in new ways of learning. To some distance learners, this new learning environment is accepted and does not impede learning. Yet, to others, distance learning is not just a plea of knowledge, but a plea for the continuous presence of the lecturer for learning to take place. Some previous studies shared that the infrequent face-to-face meetings between a lecturer and students have caused frustrations that sometimes impede the learning process (Anne & Hisham, 2016). Another study stated that the utilization of a new learning system may involve the reassessment and reengineering of the educational process (Mahendra & Andryzal, 2017). Some of the lecturers may not be able to cope with this new system because they are not ready, yet they have been forced to practice the new learning process utilising the latest technology (Kin et al., 2022).

The accessibility of the internet and the flexibility of online courses have made online education an integral part of higher education (Luyt, 2013). The ODL concept may be seen as a method of learning using technologies that merge telecommunications, information, and digital technology with its services. This is supported by a previous study that argued e-learning is best known as "pedagogy empowered by digital technology" (Mohd Azizol, 2001). As it is aimed for academic staff proficiency and participation in transferring knowledge through the technologies, ODL systems have benefited by encouraging the academic staff to be technology-savvy and to be involved when using it. Although Malaysia has adopted this teaching and learning program many years ago, education institutions are still working hard to ensure the readiness and effectiveness of the academic staff and the students.

This study fulfilled the needs to identify the intention behaviour of academic staff to use ODL technology by integrating two theories: Technology Acceptance Model (TAM) and Technology Readiness. By investigating all these, it is hoped that this study will help the management of the university to improve current technology for ODL and develop a new strategy to improve teaching and learning performance among the academic staff and also students. Therefore, the study sought to examine the following research questions:

Research Question$_1$: Is there any significant influence between academic staff technology acceptance and intention to use ODL technology?

Research Question$_2$: Does technology readiness moderate the relationship between academic staff technology acceptance and intention to use ODL technology?

2. Literature Review

The purpose of this study is to investigate the direct effects of intention behaviour to use ODL technology among the academic staff during COVID-19 pandemic using the Technology Acceptance Model (TAM) which incorporates technology readiness dimensions; optimism, innovativeness, discomfort, and insecurity as a moderating effect.

2.1 Technology Acceptance Model (TAM)

TAM was derived from the Theory of Reasoned Action (TRA) by Ajzen and Fishbein (Davis, 1989), that discussed how attitude influenced behaviour. According to Davis (1989), perceived usefulness is defined as the degree to which an individual believes that using a particular information system would improve his or her job performance. Meanwhile, perceived ease of use was defined as the degree to which an individual believes that using a particular information system would be free of effort. Behavioural intention predicts system acceptance and actual usage (Davis, Bagozzi & Warshaw, 1989; Venkatesh, Morris, Davis & Davis, 2003).

A previous study by Ong (2019) defined behavioural intention as the cognitive representation of a person's readiness to perform some specified future behaviour. Many studies have been conducted in the education field to investigate the adoption of digital learning using TAM. The results have shown that perceived usefulness and perceived ease of use of computer significantly influenced intention to use technology (Mutambara & Bayaga, 2021; Al-Okaily et al., 2020; Bhattarai & Maharjan, 2020; Pal & Vanijja, 2020; Thongkoo, Daungcharone & Thanyaphongphat, 2020; Estriegana, Medina-Merodio & Barchino, 2019). The theory was chosen for this study because it is a well-established technology acceptance model that has been used by other researchers to determine the factors that predict ODL technology acceptance (UFUTURE and Google Classroom) among academic staff in UiTM.

In mobile learning context, perceived ease of use was defined as users will be free from effort to adopt the mobile learning technology (Mutambara & Bayaga, 2021). Meanwhile, perceived usefulness was defined as the perception of an academic that using technology for learning will improve or boost student's performance (Mutambara & Bayaga, 2021). The intention to use the ODL technology for teaching and learning will be enhanced, if the academic staff perceive that the ODL technology suggested by the university has no difficulty to use and that it will improve teaching and learning process, and consequently improve their performance (Abdullah, Roslim & Mohd Salleh, 2022; Garcia, Lopez & Castillo, 2019). Thus, the following hypotheses were postulated:

H_1: Perceived ease of use positively influences ODL technology acceptance among the academic staff
H_2: Perceived usefulness positively influences ODL technology acceptance among the academic staff

2.2 Technology Readiness

According to Parasuraman (2000, pg. 308), Technology Readiness (TR) is defined as *"people's propensity to embrace and use new technologies to accomplish goals in home life and at work"*. Likewise, TR is able to measure whether an individual is ready to use new technologies (Chang & Chen, 2021). This is particularly so after COVID-19 pandemic that the teaching and learning process has been implemented virtually. Previous studies used TR to explore an individual's readiness to use technology through a combination of positive and negative personal opinions on technology. It has also been found to be a rather strong indicator of technical intentions and behaviours, particularly in the field of e-services (Chang & Chen, 2021; Parasuraman & Colby, 2015; Godoe & Johansen, 2012).

There are four dimensions involved in technological readiness, namely optimism, innovation, discomfort and insecurity. This study has adopted both positive and negative sides of TR dimensions as suggested by Parasuraman (2000). The optimism dimension is a positive belief of a person about technology to increase control, efficiency and flexibility on someone's performance in the workplace and home (Chang & Chen, 2021). If the academic staff expect the ODL technology to be good and beneficial, optimism will affect their decision to use ODL technology for teaching and learning. Therefore, the following hypothesis is postulated:

H_3: Optimism positively influences ODL technology acceptance among the academic staff

Likewise, innovativeness dimension is also a positive view of technology, which is the tendency to be a technological pioneer and an opinion leader (Lin & Chang, 2011). If the academic staff perceive the ODL technology as new and innovative, this influences their readiness to use the technology for teaching and learning process. Based on this review, the study developed the following hypothesis:

H_4: Innovativeness positively influences ODL technology acceptance among the academic staff

In TR, insecurity and discomfort are two dimensions associated with negative perceptions. The insecurity dimension denotes a person's mistrust of technology for all security and privacy reasons (Chang & Chen, 2021). This study defines insecurity as how the academic staff perceive the ODL technology as vulnerable or prone to danger, which is negatively influencing them to use technology.

Meanwhile, according to Parasuraman (2000), discomfort dimension refers to the perception of the system as discouraging. Discomfort gives a perceived lack of control over technology and a feeling of being overwhelmed by it. If the academic staff perceive the ODL technology as discouraging to use or a factor causing mental or body distress, it will decrease intention to use ODL technology among them as well (Abdullah et al., 2022). Thus, the following hypotheses were postulated:

H_5: Insecurity negatively influences ODL technology acceptance among the academic staff
H_6: Discomfort negatively influences ODL technology acceptance among the academic staff

Previous studies argued that people with high scores of technology readiness are skilled, excited and comfortable with innovative technologies. Besides, they also do not experience difficulties to use this new technology. On the other hand, people with low scores of technology readiness are likely to be sceptical and nervous, hence avoid using new technologies (Chang & Chen 2021). Previous studies also treated TR as a moderating effect to theorize the differences between sample groups (Chang & Chen, 2021; Suna, Leeb, Lawc & Hyund, 2020; Lin, Shih & Sher, 2007). Apart from testing the direct effect of TR on intention to use ODL technology, the TR dimensions can also be used to moderate the relationship between TAM constructs and intention to use ODL technology among the academic staff. This study proposed a research framework by integrating these two theories (TAM and TR) as shown in Figure 1.

Acceptance factors such as ease of use and usefulness of the technology used for teaching and learning play an important role to influence academic staff to adopt the technology, especially for ODL (Mohamed Jamrus & Razali, 2021)**.** From the positive point of view, the academic staff with high levels of TR have their intention to use the indicated technology for ODL process to be increased. They believe that this technology will improve their teaching and learning performance, in particular using the ODL technologies as they are easy to use. Similarly, the academic staff enjoy more during ODL as they have the right skills to interact with the latest technology so as to effectively perform their teaching and learning process.

Meanwhile, from the negative point of view, even though the academic staff feel that the latest technology is easy to use and may improve their teaching performance, their intention to use the ODL technology may decline. This could probably be when they experience security threat and feel discomfort to use the latest technology. Based on the reviews, the study posits the relationship between perceived ease of use and perceived usefulness with regard to ODL. The intention to use will be stronger in a condition of high levels of TR in terms of innovativeness and optimism, coupled with lower level of discomfort and insecurity. Thus, the following hypotheses were postulated:

H_7: The relationship between perceived usefulness and intention to use ODL technology will be stronger if discomfort towards technology is lesser
H_8: The relationship between perceived ease of use and intention to use ODL technology will be stronger if discomfort towards technology is lesser
H_9: The relationship between perceived ease of use and intention to use ODL technology will be stronger with high innovativeness behaviour
H_{10}: The relationship between perceived usefulness and intention to use ODL technology will be stronger with high innovativeness behaviour
H_{11}: The relationship between perceived ease of use and intention to use ODL technology will be stronger if insecurity towards technology is lesser
H_{12}: The relationship between perceived usefulness and intention to use ODL technology will be stronger if insecurity towards technology is lesser
H_{13}: The relationship between perceived ease of use and intention to use ODL technology will be stronger with high optimism towards technology
H_{14}: The relationship between perceived usefulness and intention to use ODL technology will be stronger with high optimism towards technology

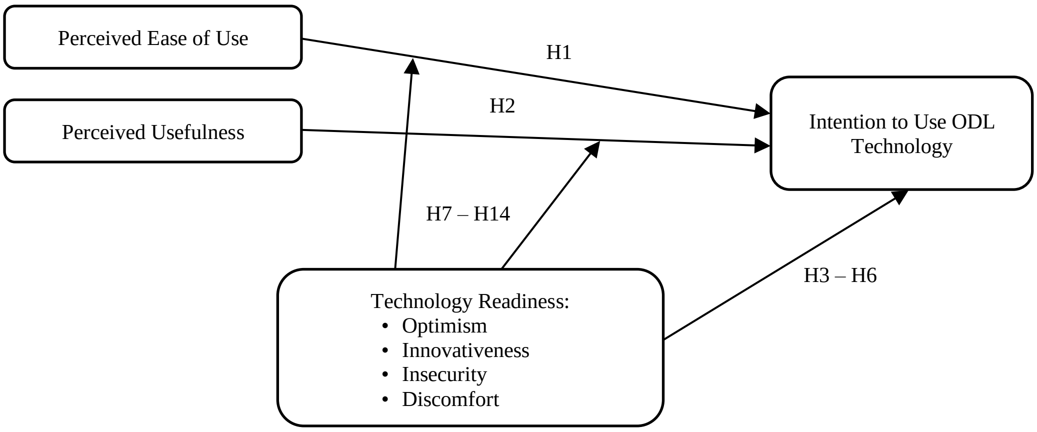

Fig.1 Theoretical Framework

Adapted from Davis (1989) and Parasuraman (2000)

3. Methodology

The study population was the academic staff in UiTM Cawangan Selangor, which included five branches, namely Puncak Alam Campus, Sungai Buloh Campus, Puncak Perdana Campus, Selayang Campus and Dengkil Campus. There are 16 faculties and six departments involved in this study. The respondents of this study have included professors, associate professors, senior lecturers and lecturers. Table 1 below displays the population of the study:

Table 1. The population of academic staff in UiTM Cawangan Selangor

No	UiTM Campus	Faculties/Departments	Total Number of Academic Staff
1.	Puncak Alam Campus	Faculty of Architecture, Planning and Surveying	305
		Faculty of Art and Design	167
		Faculty of Business and Management	277
		Faculty of Health Science	110
		Faculty of Hotel and Tourism Management	80
		Faculty of Pharmacy	85
		Faculty of Accountancy	148
		Faculty of Education	91
Total Number of Academic Staff			1263
2.	Sungai Buloh Campus	Faculty of Medicine	194
		Faculty of Dentistry	137
Total of Academic Staff			331
3.	Puncak Perdana Campus	Faculty of Film, Theater & Animation	50
		Faculty of Information Management	75
Total Number of Academic Staff			125
4.	Selayang Campus	Department of Primary Care Medicine	15
		Department of Psychology & Behavioral Medicine	16
Total Number of Academic Staff			31
5.	Dengkil Campus	Faculty of Law	16
		Faculty of Computer Sciences and Mathematics	12
		Biology Department	19
		Physic Department	25
		Chemistry Department	25

No	UiTM Campus	Faculties/Departments	Total Number of Academic Staff
		Mathematics Department	21
		Tesl Department	14
		APB Department	23
Total Number of Academic Staff			155
Overall Total Number of Academic Staff in UiTM Cawangan Selangor			1905

Note: Data retrieved from https://www.uitm.edu.my

This study employed two types of sampling techniques. First, the purposive sampling technique was used to filter out irrelevant responses that do not fit into the context of the study. The target respondents of the study were the academic staff from UiTM Selangor who have the experience using UiTM UFUTURE or Google Classroom for ODL. Next, a simple random sampling technique was used to select the respondents from UiTM academic staff email lists.

GPower calculation software was used to calculate the minimum sample size for the study. Since the model has a maximum of 14 predictors (Figure 1) with the effect size being small (0.15) and the power needed at 0.85, thus the minimum sample size required was 148. Based on this, the total sampling requirement has been fulfilled for the study.

The online survey of the questionnaire is made up via the Google Form and emailed to respondents' email addresses. For ethical considerations, several issues have been considered, including the statement of confidentiality and informed consent for participants. The analysis of the study has begun with analysing the profile of the respondents using IBM Statistical Package for Social Sciences (SPSS) version 26. The IBM SPSS was also used for data cleaning and normality testing. For model assessment, Partial Least Square-Structural Equation Modelling (PLS-SEM) version 3.3 was used to test the measurement model and structural model of the study which is discussed in the next section.

4. Data Analysis and Result

A total of 321 academic staff of UiTM Selangor responded to the questionnaire via Google Form that has been emailed to them. Majority of the respondents are female (n = 211) compared to male (n = 110). In terms of age, the majority of the respondents are in the category of over 40 years of age (n = 186) compared to those who are below 40 years of age (n = 135). Majority of the respondents have Master’s Degree (n = 172), followed by PhD/DBA (n = 145) and Bachelor’s Degree (n = 4).

Majority of the respondents are in the senior lecturer position (n= 171) followed by lecturer (n = 63), professor (n = 62) and associate professor (n = 25). Majority of these respondents are from the Faculty of Dentistry (n = 83), UiTM Selangor, Malaysia. In terms of academic experience, majority of the respondents are experienced as academic staff in UiTM; having more than 10 years (n = 178) compared to less than or equal to 10 years (n = 143). Majority of these respondents use Google Classroom as the main platform for managing their ODL. The details of the respondent’s profile are presented in Table 2.

Table 2. Demographics Details

		Frequency	Percent
Gender			
	Male	110	34.3
	Female	211	65.7
Age Group			
	25-29 years	3	0.9
	30-39 years	132	41.1
	40-49 years	125	38.9
	50-59 years	45	14.0
	60 and above	16	5.0
Education Level			

	Frequency	Percent
Bachelor's Degree	4	1.2
Master's Degree	172	53.6
PhD/DBA	145	45.2
Position		
Lecturer	63	19.6
Senior Lecturer	171	53.3
Associate Professor	25	7.8
Professor	62	19.3
Faculty Name		
Architecture, Planning & Surveying	8	2.5
Art & Design	6	1.9
Business Management	25	7.8
Health & Science	48	15.0
Hotel & Tourism Management	36	11.2
Pharmacy	37	11.5
Accountancy	5	1.6
Education	26	8.1
Dentistry	83	25.9
Medicine	6	1.9
Film, Theatre & Animation	8	2.5
Law	20	6.2
Applied Science	3	0.9
Information Management	2	0.6
Computer Sciences & Mathematics	8	2.5
Teaching Experience		
1-5 years	36	11.2
6-10 years	107	33.3
11-15 years	84	26.2
16-20 years	42	13.1
21-25 years	29	9.0
26-30 years	10	3.1
31 and above	13	4.0
Teaching Tools Used		
UiTM UFUTURE	121	37.7%
Goggle Classroom	200	62.3%

4.1 Common Method Bias (CMB)

This study used the technique of Harman's single factor to examine potential of Common Method Bias (CMB). According to the suggestions of prior research (Podsakoff & Organ, 1986; Mattila & Enz, 2002), the variance for each factor should not exceed 50%. The Harman's single factor result shows that the variance for each factor ranges from 3.02% to 34.56%. Although the results met the threshold value of 50%, this study also further tested the variance inflation factors (VIFs) to examine CMB (Shiau et al., 2020). The VIF for each construct ranges from 1.40 to 2.4, which are less than the threshold of 5 (Kline, 1998). Therefore, CMB is not a problem in the study.

4.2 Measurement Model

The PLS-SEM technique was used in this study as this technique is suitable for testing the effect of the moderator proposed. It can be effectively compared to covariance-based structural equation modelling (CB-SEM) (Hair, Sarstedt, Ringle & Gudergan, 2017). The measurement model was tested to assess its reliability, convergence validity and discriminant validity (Hair et al., 2017). This technique is called confirmatory factor analysis (CFA). The reliability and validity test results have shown that the composite reliabilities (CR) for each construct ranged from 0.783 to 0.968, which exceeded the threshold value of 0.7. Meanwhile, the average variance extracted (AVE) for each construct ranged between 0.555 until 0.857, which is greater than 0.5. Thus, the cut-off values ensure that at least 50% or more of the variances in the construct are explained by the set of indicators. The collected data had been verified for its reliability by calculating the Cronbach's Alpha (CA). The resulting value ranged from 0.633 to 0.958, which is acceptable. The details of construct's reliability and validity are presented in Table 3. The results of the measurement model show that all the seven constructs are valid measures based on their parameter estimates and statistical significance (Hair et al., 2014).

Table 3. Construct Reliability and Validity

	Cronbach's Alpha	Composite Reliability	Average Variance Extracted
DISCOMFORT	0.633	0.783	0.555
INNOVATIVENESS	0.895	0.923	0.706
INSECURITY	0.854	0.895	0.681
INTENTION BEHAVIOUR	0.958	0.968	0.857
OPTIMISM	0.891	0.920	0.697
PEOU	0.854	0.897	0.639
PU	0.901	0.931	0.772

PEOU – Perceived Ease of Use, PU – Perceived Usefulness

The CFA results have shown that most of the indicators measuring a particular construct had loading values of more than 0.6 on their respective constructs (Table 4). The results confirmed that the indicators were valid for their respective constructs (Hair et al., 2014). Additionally, the discriminant validity was also tested to ensure there was no multicollinearity issue existed in this study. This was done using Heterotrait-Monotrait Ratio (HTMT) technique by examining *r* correlation value between the constructs. The results as displayed in Table 5 show that *r* correlation values between the indicated constructs were below 0.85, indicating adequate discriminant validity. Hence, this can be concluded that there is no overlapping construct exists.

Table 4. Cross Loading

CONTRUCT ITEMS	DISC	INNO	INSEC	OPT	PEOU	PU	IB
DISCOMFORT_1	0.598	0.019	0.534	0.074	0.044	0.050	0.048
DISCOMFORT_4	0.920	0.001	0.389	0.067	0.086	0.140	0.151
DISCOMFORT_5	0.679	-0.070	0.354	0.023	0.063	0.077	0.072
INNOVATIVENESS_1	0.045	0.759	0.056	0.611	0.477	0.441	0.559
INNOVATIVENESS_2	0.060	0.844	0.012	0.575	0.473	0.447	0.481
INNOVATIVENESS_3	-0.055	0.849	0.010	0.455	0.341	0.350	0.404
INNOVATIVENESS_4	-0.083	0.880	-0.005	0.510	0.353	0.328	0.507
INNOVATIVENESS_5	-0.054	0.862	-0.006	0.525	0.368	0.435	0.520
INSECURITY_1	0.430	0.030	0.893	0.060	0.045	0.015	0.085
INSECURITY_3	0.432	-0.072	0.722	-0.022	-0.020	-0.010	0.020
INSECURITY_4	0.431	0.008	0.798	0.086	0.045	0.021	0.082
INSECURITY_5	0.415	0.036	0.876	0.017	-0.020	-0.007	0.047

CONTRUCT ITEMS	DISC	INNO	INSEC	OPT	PEOU	PU	IB
OPTIMISM_1	0.025	0.481	0.039	0.787	0.417	0.470	0.522
OPTIMISM_2	0.106	0.562	0.060	0.891	0.476	0.559	0.665
OPTIMISM_3	0.026	0.553	0.014	0.832	0.410	0.445	0.625
OPTIMISM_4	0.074	0.500	0.071	0.774	0.311	0.374	0.454
OPTIMSM_5	0.063	0.588	0.083	0.884	0.461	0.450	0.660
PEOU_1	0.118	0.392	0.012	0.440	0.860	0.547	0.543
PEOU_2	0.069	0.439	0.046	0.440	0.870	0.504	0.535
PEOU_3	0.034	0.363	0.026	0.375	0.809	0.439	0.525
PEOU_4	0.079	0.482	-0.026	0.496	0.824	0.578	0.566
PEOU_5	0.060	0.226	0.084	0.219	0.606	0.277	0.398
PU_1	0.100	0.417	0.005	0.446	0.490	0.909	0.622
PU_2	0.099	0.395	0.005	0.484	0.539	0.907	0.620
PU_3	0.134	0.372	-0.027	0.444	0.604	0.876	0.604
PU_5	0.140	0.508	0.062	0.572	0.469	0.819	0.613
INT_1	0.112	0.541	0.069	0.642	0.647	0.621	0.951
INT_2	0.148	0.477	0.073	0.596	0.587	0.653	0.933
INT_3	0.087	0.614	0.075	0.693	0.631	0.677	0.940
INT_4	0.182	0.563	0.114	0.667	0.544	0.646	0.871
INT_5	0.123	0.560	0.057	0.686	0.582	0.642	0.930

Table 5. Discriminant Validity (HTMT)

CONSTRUCT	DISC	INNOV	INSEC	IB	OPT	PEOU	PU
Discomfort (DISC)							
Innovativeness (INNO)	0.103						
Insecurity (INSEC)	0.779	0.059					
Intention Behaviour (IB)	0.154	0.634	0.078				
Optimism (OPT)	0.104	0.712	0.070	0.758			
Perceived Ease of Use (PEOU)	0.119	0.541	0.077	0.714	0.561		
Perceived Usefulness (PU)	0.156	0.531	0.038	0.754	0.615	0.673	

4.3 Structural Model

The structural model was tested by assessing the significance and magnitude of the hypothesized relationships using bootstrapping procedure. Table 5 summarizes the hypothesis testing results. The results show that the proposed model can explain 69% (R^2 = 0.687) of behavioural intention to use ODL technology among the academic staff. Based on direct testing result, all the hypotheses were supported (H1 – H4), except the results for H5 and H6 were insignificant. The highest contribution of this study was Optimism (*B = 0.363*, *t-value = 6.973****, f^2 *= 0.188*), followed by Perceived Usefulness (PU) (*B = 0.288*, *t-value = 5.388****, f^2 *= 0.169*), Perceived Ease of Use (PEOU) (*B = -0.156*, *t-value = 5.752****, f^2 *=0.095*) and Innovativeness of the academic staff (*B = 0.117*, *t-value = 2.496***, f^2 *= 0.023*). Optimism and PU have a medium effect on behavioural intention to use ODL technology among the academic staff in UiTM, while PEOU and Innovativeness have a small effect. This indicated that if the academic staff believe in technology that they use for ODL can improve their teaching and learning performance, it will lead to their intention to use it.

The moderating effect results show that Discomfort negatively strengthened the relationship between PU and intention behaviour to use ODL technology (B = 0.288, p-value = 0.00, f^2 = 0.381). The interaction plot shows that the PU effect is stronger when the level of Discomfort is low. Likewise, Optimism positively moderated the relationship between PU and intention behaviour to use ODL technology (B = 0.097, p-value = 0.05, f^2 = 0.336). Based on the interaction plot, the result shows that the effect of PU is stronger when the level of optimism is high. Another dimension of Technology Readiness (Innovativeness) influenced the moderating effect between both technology acceptance factors: PU (B = -0.103, p-value = 0.05, f^2 = 0.354) and PEOU (B = 0.111, p-value = 0.02, f^2 = 0.350), and the intention behaviour to use ODL technology among the academic staff. The interaction plot result also shows that the effect of PU and PEOU is stronger when the level of innovativeness is high.

Based on the overall results, there is sufficient evidence to conclude that H7, H9, H10 and H14 were supported with a large effect size (Discomfort, Optimism and Innovativeness), while H8, H11 to H13 were not supported. After removing the moderating variables (Technology Readiness Dimensions) from the model, the value of R^2 only sees a slight drop from 70.7% to 68.7%, which implies that these moderating variables only accounted for the marginal variance (9%) in ODL technology intention. Therefore, it can be concluded that Technology Readiness does significantly impact the research model. The details of the hypothesis testing results can be seen in Table 5, as well as in Figures 2(a) and 2(b). Meanwhile, the interaction plot results are presented in Figures 3(a – d).

Table 5. Hypothesis Testing

	Hypothesis	B	t	p	5%	95%	f^2	R^2	Result
(a)	Direct Effect Testing							68.7%	
H1	PEOU -> INTENTION BEHAVIOUR	0.251	5.752	0.000	0.174	0.315	0.095		Supported
H2	PU -> INTENTION BEHAVIOUR	0.288	5.388	0.000	0.197	0.376	0.169		Supported
H3	OPTIMISM -> INTENTION BEHAVIOUR	0.363	6.973	0.000	0.279	0.453	0.188		Supported
H4	INNOVATIVENESS -> INTENTION BEHAVIOUR	0.117	2.496	0.006	0.041	0.194	0.023		Supported
H5	INSECURITY -> INTENTION BEHAVIOUR	0.026	0.710	0.239	-0.033	0.088	0.002		Not Supported
H6	DISCOMFORT -> INTENTION BEHAVIOUR	0.031	0.782	0.217	-0.032	0.096	0.004		Not Supported
(b)	Moderating Effect Testing							77.7%	
H7	DISC*PU -> INTENTION BEHAVIOUR	-0.156	2.712	0.003	-0.230	-0.051	0.381		Not Supported

	Hypothesis	*B*	t	p	5%	95%	*f*^{2}	*R*^{2}	Result
H8	DISC*PEOU -> INTENTION BEHAVIOUR	0.073	1.331	0.092	-0.028	0.155	0.318		Not Supported
H9	INNO*PEOU -> INTENTION BEHAVIOUR	0.111	2.021	0.022	0.027	0.200	0.350		Supported
H10	INNO*PU -> INTENTION BEHAVIOUR	-0.103	1.635	0.051	-0.208	-0.005	0.354		Supported
H11	INSEC*PEOU -> INTENTION BEHAVIOUR	-0.003	0.061	0.476	-0.082	0.091	0.331		Not Supported
H12	INSEC*PU -> INTENTION BEHAVIOUR	0.020	0.355	0.361	-0.101	0.093	0.331		Not Supported
H13	OPTI*PEOU -> INTENTION BEHAVIOUR	-0.056	0.983	0.163	-0.162	0.024	0.350		Not Supported
H14	OPTI*PU -> INTENTION BEHAVIOUR	0.097	1.691	0.046	0.010	0.200	0.336		Supported

Note: Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Innovativeness (INNO), Optimism (OPTI), Insecurity (INSEC) and Discomfort (DISC)

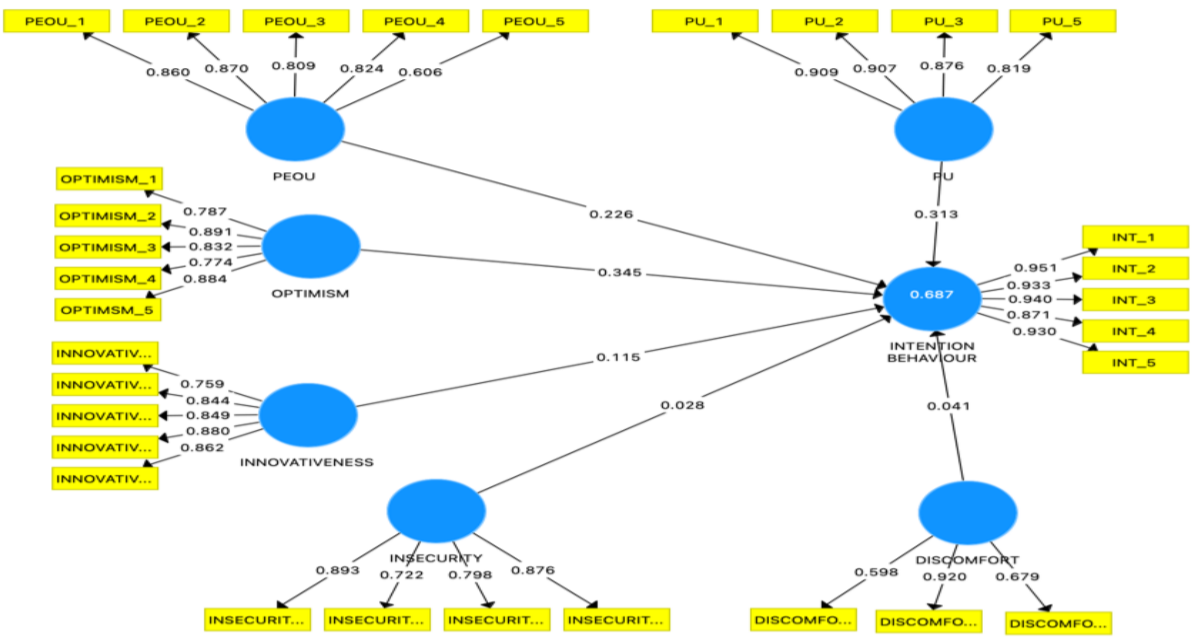

Fig. 2(a). Hypothesis Testing Result without Moderating Effect

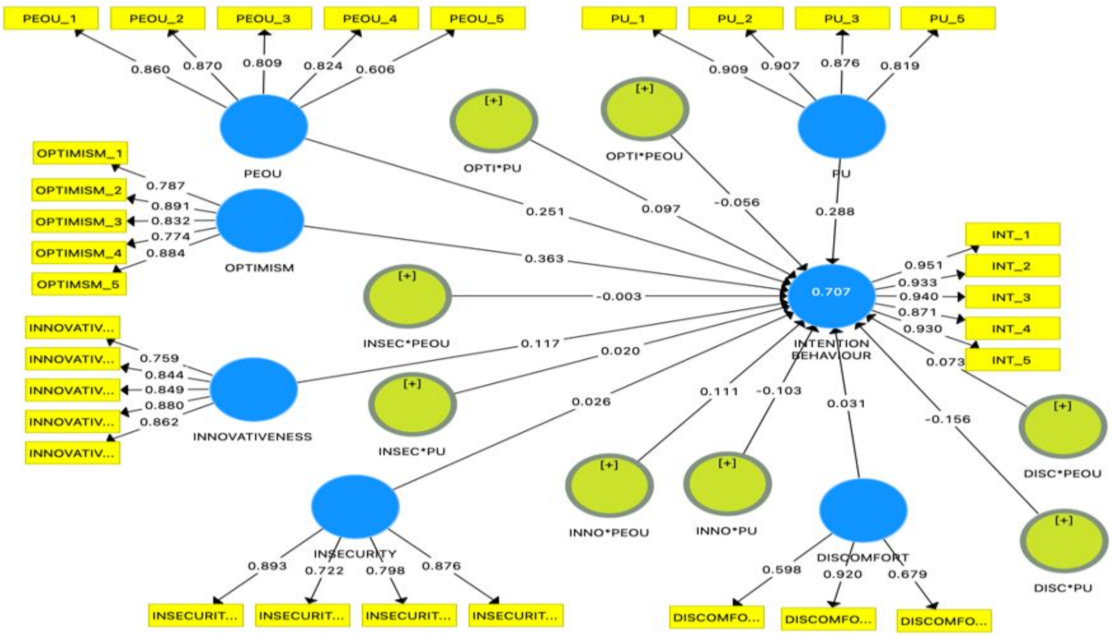

Fig. 2(b). Hypothesis Testing Result with Moderating Effect

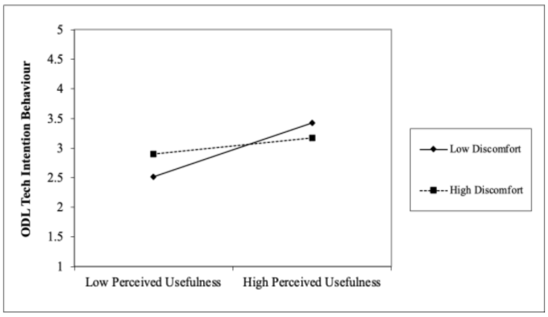

Fig. 3(a). PU x Discomfort

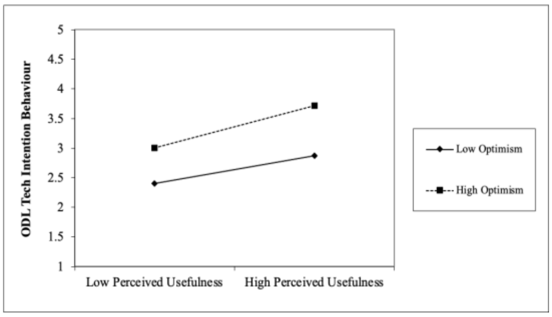

Fig. 3(b). PU x Optimism

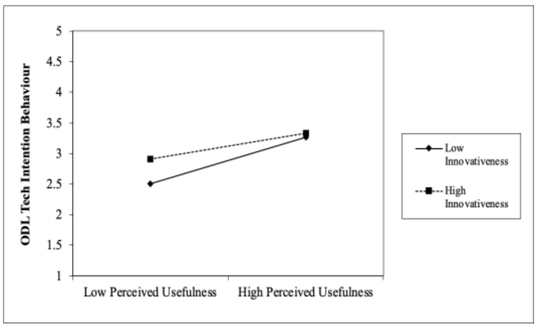

Fig. 3(c). PU x Innovativeness

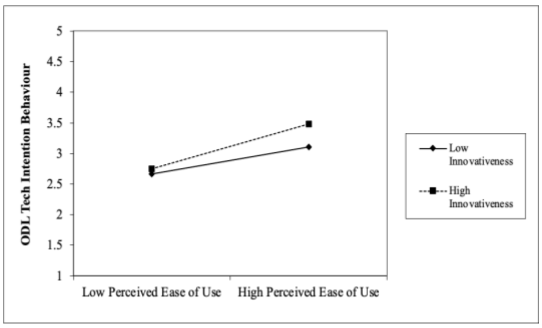

Fig. 3(d). PEOU x Innovativeness

5. Discussion

The study was motivated by the need to better understand the role of Technology Readiness and Technology Acceptance in ODL, in particular when the learning institution is transforming from the traditional method of teaching and learning to a new method which is online learning. This new transformation is not only about delivering the teaching and learning materials to the students, but also handling and managing attendance records, assessment marks and several others.

The results show that all the direct hypotheses from the research model are confirmed to be significant, except for the two factors of Technology Readiness which are Insecurity and Discomfort. Perceived Usefulness is shown to be the most significant factor that directly affects intention behaviour to use ODL technology among the academic staff in UiTM. Meanwhile, for the Technology Readiness factor, Optimism is shown to have a medium effect on intention behaviour to use ODL technology compared to the other factors of Technology Readiness. In terms of moderating effect, the result has shown that Technology Readiness (Optimism, Innovativeness and Discomfort) can moderate the relationship between Perceived Ease of Use and intention behaviour to use ODL technology, and also between Perceived Usefulness and intention behaviour to use ODL technology. However, most of the respondents do not feel that their insecurity behaviour towards ODL technology can give an impact on the relationships among technology acceptance factors. The result of this study has shown that this factor (Insecurity) was insignificant.

In the context of ODL technology intention to use, the focus is on two types of ODL technology platform, namely UFUTURE and Google Classroom. The result shows that 69% of the variance in intention behaviour to use ODL technology was explained by the technology acceptance factors and technology readiness factors. Perceived Usefulness has a medium effect on intention behaviour to use ODL technology which is consistent with most of the previous literature related to technology use (Chang & Chen, 2021; Tsourela & Roumeliotus, 2015; Lin & Chang, 2011). This can be concluded that if the academic staff believe the new technology of the ODL platform can improve the way they handle and manage teaching materials and coursework assessments, they will be more likely to use the suggested technology that can be used for teaching and learning, particularly when the university has introduced ODL concept (Kin et al., 2022; Mohamed Jamrus & Razali, 2021).

On the other hand, Perceived Ease of Use is shown to have a small effect on intention behaviour to use the ODL technology platform. Previous studies have proven that this factor is one of the important factors to trigger users to use the related technology (Chang & Chen, 2021; Nuguho & Fajar, 2017). This study suggests that the more the academic staff perceive the ODL technology that they need to use as useful and easy to use, the more favourable their behaviour to use that technology which is suitable for their teaching and learning process.

The research findings also support that Optimism towards technology contributes to the medium effect on intention behaviour to use ODL technology. Meanwhile, Innovativeness is shown to have a small effect among others. In this study, optimism is related to the academic staff who believe in the flexibility, convenience and efficiency of the ODL technology that can be used for teaching and learning. Based on the result, it is confirmed that most academic staff are optimistic when it comes to technology use for teaching and learning in ODL. Optimistic people are those who are confident that the technology is under their control (Omotayo & Adekunle, 2020). Therefore, the management must seriously consider the efficiency and flexibility of the proposed technology that will be implemented in the university. Technology issues such as system failure, internet connectivity and system malfunction should be taken care of thoroughly by the technical team in the university before the ODL system is implemented in the university.

Most lecturers are innovative and are open to new ideas related to technology innovation (Omotayo & Adekunle, 2020). The result also confirmed that Innovativeness significantly affected intention behaviour to use ODL technology among academic staff. Likewise, the findings of this study also supported by the previous studies related to technology use (Omotayo & Adekunle, 2020; Nuguho & Fajar, 2017; Tsourela & Roumeliotus, 2015). Furthermore, the study has also found that Insecurity and Discomfort insignificantly affected intention behaviour to use ODL technology. The findings contradicted with the results found in previous studies (Omotayo & Adekunle, 2020; Khaushik & Agrawal, 2020). The contradiction of these results might be due to the respondent’s profile.

Previous studies focussed on students and academic staff perception related to the online learning and e-voting system. Meanwhile, this study also focussed on the ODL platform that is used by the lecturers for teaching and learning during COVID-19 pandemic year. Nevertheless, most of the academic staff are ready with the technology that they will use if the ODL is implemented in the university. On top of that, the academic staff also have been trained to use the related technology organized by the university for this ODL preparation. Therefore, they did not fear to adopt this new technology for teaching and learning. Trust factor towards university management perhaps plays an important role whereby future researcher should explore further on this factor for investigating technology acceptance among the academic staff.

Previous study has also employed Technology Readiness as a second-order factor and being used as a single moderating variable (Chang & Chen, 2021). However, this study used the dimensions of technology readiness as a separate moderator. In terms of the moderating effect of Optimism, this study has found that Optimism positively moderated the relationship between Perceived Usefulness and intention behaviour to use ODL technology. The result shows that lecturers with high optimism, the perceived usefulness will have a stronger impact on intention behaviour to use ODL technology. However, Optimism does not moderate the relationship between perceived ease of use and intention behaviour to use ODL technology in the context of higher education.

Furthermore, Innovativeness is shown to have a larger effect on strengthening the relationship between both technology acceptance factors (Perceived Ease of Use and Perceived Usefulness) and intention behaviour to use ODL technology. Lecturers with high innovative will give an impact on ODL technology acceptance. Likewise, many lecturers have been trained to be more open to new ideas and to be more innovative especially in teaching and learning. Therefore, it was not surprising if this factor plays an important role in technology acceptance.

Contrary to the research hypotheses, Insecurity has no significant moderating effect on the relationships between technology acceptance factors and intention behaviour to use ODL technology. This is perhaps due to the trust factor among the academic staff towards the management of the university. The academic staff feel that security is not an issue for them to accept the new technology, particularly when they feel that this technology will provide many benefits for them to handle and manage teaching and learning during ODL environment.

6. Conclusion

TAM has been widely employed by many researchers to study technology acceptance (Chang & Chen, 2021; Muatmbara & Bayaga, 2021; Nuguho & Fajar, 2017; Tsourela & Roumeliotus, 2015). However, there are few studies that investigated the role of technology readiness as a moderator in the technology acceptance context (Omotayo & Adekunle, 2020; Tsourela & Roumeliotis, 2015). Meanwhile, many studies have confirmed that Technology Readiness plays an important role to enhance user’s intention behaviour to use new technology (Chang & Chen, 2021; Omotayo & Adekunle, 2020; Rafique et al., 2018; Tsourela & Roumeliotis, 2015). The rise of the COVID-19 pandemic issue globally has introduced the Movement Control Order (MCO) which has been enforced since early 2020. Many higher institutions have also moved from Work from Office (WFO) to Work from Home (WFH). It was during the WFH, the teaching and learning process has begun to take place virtually. Taking this into consideration, this study has also developed the research model by integrating two concepts (Technology Acceptance and Technology Readiness) which aimed to investigate the intention behaviour to use ODL technology among academic staff in UiTM.

Based on the research findings, eight hypotheses were accepted and six hypotheses were rejected. The results have also found that Perceived Usefulness and Optimism towards ODL technology contributed medium effect compared to other factors proposed in the model. Likewise, the moderating role of technology readiness is shown to have a large effect on ODL technology acceptance among academic staff in UiTM. This can be concluded that the management of the university must seriously consider the indicated factors that have been discussed in the previous section. All these factors are important to be analysed and investigated when planning the new system development for ODL.

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