



ISSN: 2617-6548

URL: www.ijirss.com



Intention of learners to continue online learning using the extended TAM framework

 Siti Haryani Shaikh Ali^{1*},  Shahrinaz Ismail²,  Yuhanis Omar³

^{1,3}*Eduainment Industrial Revolution 4.0 Research Cluster, Informatics and Analytics Section, Malaysian Institute of Technology, Universiti Kuala Lumpur, Malaysia.*

²*School of Computing and Informatics, Albukhary International University, Malaysia.*

Corresponding author: Siti Haryani Shaikh Ali (Email: sharyani@unikl.edu.my)

Abstract

This study examined the characteristics that impact students' intentions to use Microsoft Teams as their primary teaching and learning platform. A total of 171 students were randomly selected to complete an electronic questionnaire that tested the constructs of the extended Technology Acceptance Model (TAM). The results indicated that “perceived usefulness” and “attitude” towards the platform together with “perceived ease of use” ($R^2 = 73.9\%$) were the most important predictors of students' intention to use Microsoft Teams in the future ($R^2 = 77.8\%$ and 73.9% respectively). This study recommends lecturers and students communicate more to increase the student's intrinsic motivation in online learning by incorporating various activities that promote collaboration, communication and active learning in the online environment. Such activities can be facilitated by the platform and can include online discussions, peer review, group projects and collaborative problem-solving tasks. In addition, the study suggests that lecturers should provide more training and support to students on how to use MS Teams effectively to enhance their learning experience.

Keywords: Continuance intention, Extended TAM, Intrinsic motivation, Online learning, Structural equation modelling, Technology acceptance model.

DOI: 10.53894/ijirss.v6i4.2095

Funding: This research is supported by a Short-Term Research Grant from the Universiti Kuala Lumpur, Malaysia (Grant number: STR19040).

History: Received: 4 October 2022/Revised: 24 May 2023/Accepted: 11 September 2023/Published: 19 September 2023

Copyright: © 2023 by the authors. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

Authors' Contributions: All authors contributed equally to the conception and design of the study. All authors have read and agreed to the published version of the manuscript.

Competing Interests: The authors declare that they have no competing interests.

Transparency: The authors confirm that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.

Institutional Review Board Statement: The Ethical Committee of the Universiti Kuala Lumpur, Malaysia has granted approval for this study (Ref. No. UNIKL REC/2023/STRG/APV02).

Publisher: Innovative Research Publishing

1. Introduction

1.1. The Pandemic and Online Learning in Malaysia

The COVID-19 epidemic has significantly impacted traditional educational methods due to the widespread implementation of laws that restrict public gatherings. Such measures in Malaysia are known as the Movement Control Order (MCO). In Malaysia, higher education institutions have predicted that the MCO will disrupt regular teaching and learning indefinitely. Educational institutions increasingly turn to online learning to conduct learning and teaching in a safe environment. Online education is not a novel concept in Malaysia. Many public and private universities across the nation started using e-learning techniques in the early 2000s to offer academic programmes over the internet or to supplement the learning of their full-time on-campus students. Students between the ages of 16 and 18 have a more positive attitude towards e-learning than traditional learning techniques [1]. The benefits of online education are numerous including greater effectiveness achieved through discussions, greater flexibility of study, greater accessibility of lessons through multiple channels, improvement in student performance, greater course satisfaction and higher computer self-efficacy [2-6].

The Malaysian Ministry of Higher Education has recommended online learning to maintain teaching and learning during the epidemic. Few universities offered online courses before the pandemic. According to research, the majority of Malaysian higher education institutions have appropriate e-learning infrastructure but need e-learning strategy that includes information and communications technology (ICT) planning for teaching and learning, course development, course structure and course assessment [7]. According to a study by Duță and Foloștină [8], approximately 20% of online learners attend training due to a lack of incentive components.

1.2. Challenges in Online Learning

During the pandemic, it was difficult for students to maintain concentration while in online learning because the internet connection was unreliable and the teaching and learning medium was inadequate Yusuf and Ahmad [9]. Chung, et al. [10] examined online learning difficulties during the pandemic. They concluded that the most significant impediment for degree students is internet connectivity while the most significant problem for diploma students is difficulty understanding the course content.

Li and Yu [14] reported that only a few studies [11-13] investigated the continued intention to use the online learning platform. Consequently, this research aims to investigate the factors that impact learners' intentions while using online learning. The factors determining the learners' continued participation in online learning were adapted from the extended TAM model [14]. This model measures not only the acceptance of a particular technology but also the learner's attitude and its effect on the learner.

2. Technology Acceptance Model

The formation of technology acceptance theory can be traced back to the process by which new technologies are adopted and put into use. The Technology Acceptance Model (TAM) [15] which was primarily used to explain computer-usage behaviour [16] is based on the theory of reasoned action. However, there are a few different theories that describe how new technologies are accepted. According to Lee, et al. [17]; Lee [13]; Alenezi, et al. [18]; Sanchez-Franco [19] and Shroff, et al. [20], TAM has also been used as a theoretical model to describe learner behaviour in online learning (2011). The original TAM model places a strong focus on "perceived usefulness" and "perceived ease of use" as the two primary criteria that determine user acceptability and how people interact with technology [16]. According to the findings of other research on technology acceptability in online learning, perceived ease of use, perceived utility, perceived fun and perceived self-autonomy had a significant impact on learners' intentions to continue their online learning (see Table 1).

TAM was primarily employed in an online learning environment to examine TAM's two core factors, "perceived usefulness" and "perceived ease of use" as well as additional variables listed in Table 1. The added variables mainly represent intrinsic and extrinsic motivation and also provide support for using the learning platform.

3. Conceptual Framework

This study investigates the factors that influence students' intentions to use online learning after their initial exposure. TAM has been the most well-established technology adoption model. The extended TAM model also considers the learners' attitudes towards technology. In prior studies, TAM was not only altered but also numerous constructs were added based on the research aims such as flow constructs [17] and the information needs perspective [21].

Table 1.
Models for virtual learning technologies: Acceptance studies.

No	Author/Publ.	Research implication and Findings
1	Arteaga Sánchez, et al. [22]	It was found that students were able to use the platform more effectively when given technical assistance. The findings include recommendations for expanding the use of training courses and providing technical assistance to students.
2	Cheng, et al. [23]	According to the findings, the TAM model might be able to assist in explaining why the students desired to use the platform for group projects.
3	Singh, et al. [24]	The model suggests that students have a positive attitude about using the technology platform and want to use it in the near future. The key TAM features in the study are interaction and cost-effectiveness.
4	Bakhsh, et al. [25]	According to the findings, both student and faculty skill preparation as well as

No	Author/Publ.	Research implication and Findings
		self-efficacy play a role in determining how beneficial something is regarded. The findings also indicate that a person's behavioural intention to adopt mobile learning is positively influenced by both the perceived value of the mobile learning platform and previous experience.
5	Teck Soon and Kadir [26]	The model demonstrates that factors such as autonomy, competence and relatedness each have substantial bearings on factors such as trust, attitude towards knowledge sharing and behavioural intention.
6	Lee et al. [17]	According to the findings, instructor characteristics and instructional materials are determinants of e- learning's usefulness while perceived usefulness and fun are predictors of e- learning's perceived usefulness.

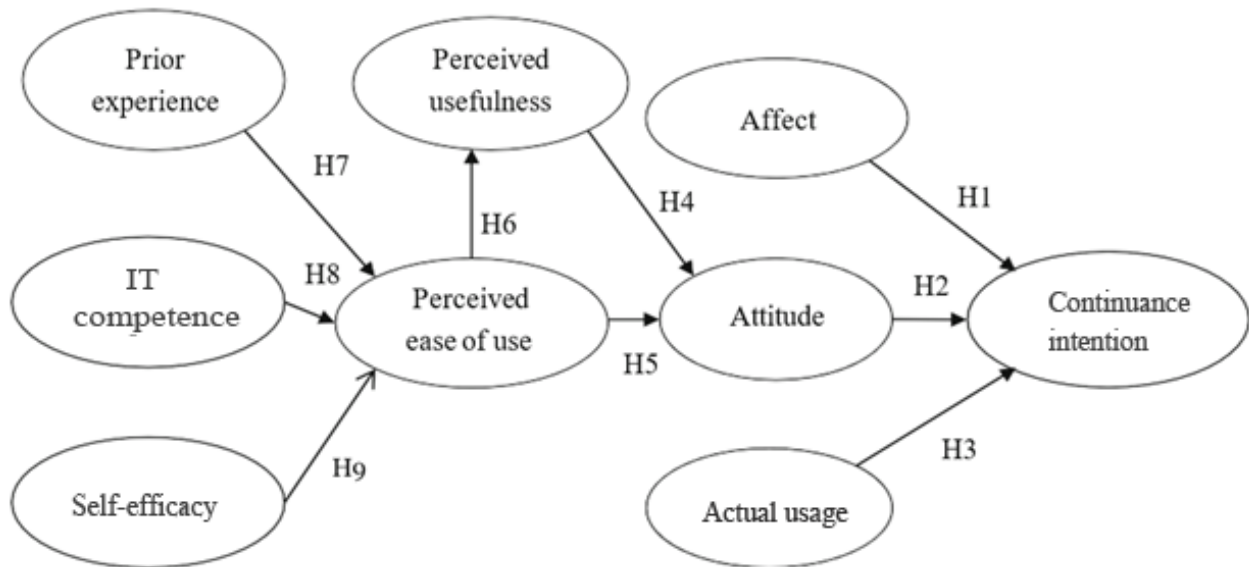


Figure 1. Conceptual framework.

The extended elements for the TAM model depicted in Figure 1 were derived from prior research that added attitude as a predictor of continuation intent Roca and Gagné [12]; Lee [13]. Alenezi, et al. [18] highlighted emotional and social elements as the primary determinants of learners' continued participation. The extended TAM model in Figure 1 includes the affect variable, the attitude variable and the actual usage variable.

Affect is an inner motivation to act and it subconsciously drives decision-making [27]. Future technology adoption was believed to be influenced by attitude, affect and actual use [14]. The fundamental TAM features of perceived utility and perceived ease of use are based on the notion that learners are more likely to engage in e-learning if they view the technology as user-friendly and beneficial. Other predictor factors for perceived ease of use included in this modified TAM model are prior experience, information technology (IT) competence and self- efficacy. These three characteristics are essential to this paradigm as the students come from diverse backgrounds and have different viewpoints on technology.

Table 2. Research hypotheses.

Hypothesis	Connection	Description
H1	AFF → CI	Affect has a positive effect on the students' continued intention to use MS Teams.
H2	ATT → CI	Attitude has a positive effect on the students' continued intention to use MS Teams.
H3	AU → CI	Actual usage has a positive effect on the students' continued intention to use MS Teams.
H4	PU → ATT	Perceived usefulness has a positive effect on the students' attitude towards using MS Teams.
H5	PEU → ATT	Perceived ease of use has a positive effect on the students' attitude towards using MS Teams.
H6	PEU → PU	Perceived ease of use has a positive effect on the perceived usefulness of MS Teams.
H7	PE → PEU	Prior experience has a positive effect on the perceived ease of use of MS Teams.
H8	IT → PEU	IT competence has a positive effect on the perceived ease of use of MS Teams.
H9	SE → PEU	Self-efficacy has a positive effect on the perceived ease of use of MS Teams.

The presence of links between constructs in the model was validated using nine hypotheses alternatives based on existing research on technology acceptance theories as shown in Table 2. They are firmly related to the presumed relationships between the constructs presented in Figure 1.

4. Methodology

4.1. Research Design

This research uses a quantitative methodology. During the pandemic, university students who used MS Teams as a platform for teaching and learning were surveyed to determine their intention to continue using the platform. To collect data on the theoretical model's underlying constructs, including intention, affect, attitude, actual usage, perceived usefulness, perceived ease of use, prior experience, IT competence and self- efficacy and a Google Form-based online questionnaire was distributed through instant messenger.

Multi-item measures based on 5-point Likert scales with anchors ranging from 1 (least agree) to 5 (strongly agree) were used to describe these constructs and the items used to measure them were adopted from previously validated scales.

Table 3.
Demographic profile of respondents (N=171)

Variable	N	Percentage (%)
Age		
20 and below	55	32.2
21 – 22	42	24.5
23-24	68	39.8
25 and above	6	3.5
Year of study		
1 st year	24	14.0
2 nd year	81	47.4
3 rd year	58	33.9
4 th year	8	4.7
Location during MCO		
Overseas	2	1.2
East Malaysia	3	1.8
East Coast (WM)	22	12.8
West Coast (WM)	60	35.1
North Coast (WM)	15	8.8
Federal territories	16	9.4

Note: WM = West Malaysia or Peninsular Malaysia, East Malaysia = Sabah, Sarawak.

4.2. Sampling and Data Collection

The data was collected during the June semester when the students experienced total lockdown due to the pandemic. Purposive sampling was employed where the questionnaire was distributed only to higher learning institutes that adopt MS Teams as their teaching and learning platform. All the questionnaire's items received responses from 171 users.

Hair, et al. [28] suggested employing a power analysis to establish the sample size before employing any structural equation modeling (SEM) models. Soper's prior-sample-size calculator for structural equation modelling was used to evaluate the sample size of this study (2017). When using this calculator, it is necessary to consider the number of measurement items, the number of exogenous and endogenous factors inside the theoretical framework and the expected impact size [29]. The following information was entered: 36 observed variables, a statistical power of 95% and a probability threshold of 0.05. According to the calculator, these factors imply a sample size of 128. Consequently, the sample size criterion for the current study is satisfied because the suggested sample size meets the aforementioned requirements.

5. Results

5.1. Descriptive Analysis of the Sample Profile

Referring to Table 3, the majority of the respondents were between the ages of 23 and 24 accounting for 39.8% of the total respondents while just 3.5 percent of the respondents were between the ages of 25 and above. Approximately 47.4 percent of the respondents were in second year while 4.7 percent were in fourth year. More than a quarter or 35.1% of the total respondents who conducted their virtual learning (using MS Teams) during the movement control order (MCO) were located in Perak, Selangor and Malacca (WM).

5.2. Constructs' Validity and Reliability

Both composite reliability and reliability tests should be examined to confirm the validity and reliability of the measurement model [28, 30]. According to Nunnally and Bernstein [31] and Fornell and Larcker [32], the Cronbach's alpha and composite reliability values for each construct are above the recommended standard of 0.7. The measurement model's reliability is attained since the Cronbach's alpha and composite reliability values are above the cut-off point (more than 0.70) offered two standards for determining the model's convergent validity Bagozzi and Yi [33]. Each variable's average variance extracted (AVE) and indicator factor loading should be greater than 0.5 [32]. In Table 4, the results show that our instrument has convergent validity. Table 4 indicates that all indicators load highest on their respective constructions and no indicator loads higher on other constructs than on the one for which it was designed. The results suggest that the square

root of the AVEs for each construct is bigger than the cross-correlation with other constructs as seen in Table 5. As a result, the instrument's discriminant validity was demonstrated.

Table 4.
Construct reliability and validity.

Construct	Measurement item	Item loadings	AVE	CR	α
Actual usage (AU)	AU1	0.918	0.847	0.943	0.912
	AU2	0.934			
	AU3	0.909			
Affect (AFF)	AFF1	0.936	0.903	0.974	0.965
	AFF2	0.949			
	AFF3	0.967			
	AFF4	0.949			
Attitude (ATT)	ATT1	0.928	0.884	0.958	0.936
	ATT2	0.947			
	ATT3	0.945			
Continuance intention (CI)	CI1	0.870	0.796	0.940	0.916
	CI2	0.933			
	CI3	0.919			
	CI4	0.844			
IT competence (IT)	IT1	0.918	0.847	0.957	0.945
	IT2	0.924			
	IT3	0.937			
	IT4	0.901			
Perceived ease of use (PEU)	PEU1	0.901	0.830	0.936	0.903
	PEU2	0.929			
	PEU3	0.902			
Perceived usefulness (PU)	PU1	0.937	0.818	0.964	0.957
	PU2	0.938			
	PU3	0.933			
	PU4	0.930			
	PU5	0.824			
	PU6	0.857			
Prior experience (PE)	PE1	0.904	0.737	0.893	0.822
	PE2	0.921			
	PE3	0.738			
Self-efficacy (SELF)	SELF1	0.790	0.677	0.926	0.919
	SELF2	0.858			
	SELF3	0.909			
	SELF4	0.888			
	SELF5	0.745			
	SELF6	0.726			

Note: CR (Composite reliability), AVE (Average variance extracted), α (Cronbach's Alpha).

Table 5.
Fornell-Larcker criterion: Discriminant validity.

Construct	Actual usage	Affect	Attitude	Continuance intention	IT competence	Perceived ease of use	Perceived usefulness	Prior experience	Self-efficacy
Actual usage	0.92								
Affect	0.56	0.95							
Attitude	0.627	0.791	0.94						
Continuance intention	0.657	0.707	0.835	0.892					
IT competence	0.44	0.55	0.608	0.598	0.92				
Perceived ease of use	0.671	0.756	0.837	0.814	0.68	0.911			
Perceived usefulness	0.757	0.744	0.834	0.866	0.631	0.883	0.904		
Prior experience	0.242	0.178	0.262	0.254	0.434	0.249	0.364	0.858	
Self-efficacy	0.606	0.601	0.658	0.649	0.653	0.672	0.716	0.41	0.823

A conventional bootstrapping approach was used with 500 resamples generated with replacement to determine the relevance of each predicted path. The coefficient of determination (R^2) and the standardised root mean square residual (SRMR) composite factor model were also used to assess the structural model's quality [35]. Results for the structural model assessment are presented in Table 6 and Figure 2.

Table 6.
Hypotheses testing and structural relationships

Hypoth.	Relationship	Std. beta	Std. error	Path coefficient	T-value	Decision	97.5 % CI LL	97.5 % CI UL
H1	Affect -> Continuance intention	0.102	0.082	0.90	1.096	Not supported	-0.026	0.298
H2	Attitude -> Continuance intention	0.622	0.086	0.632	7.347***	Supported	0.426	0.764
H3	Actual Usage -> Continuance intention	0.21	0.057	0.211	3.686***	Supported	0.104	0.313
H4	Perceived usefulness -> Attitude	0.434	0.075	0.431	5.741***	Supported	0.291	0.579
H5	Perceived ease of use -> Attitude	0.454	0.075	0.457	6.052***	Supported	0.286	0.591
H6	Perceived ease of use -> Perceived usefulness	0.883	0.02	0.883	44.886***	Supported	0.84	0.915
H7	Prior experience -> Perceived ease of Use	-0.112	0.053	-0.123	2.33**	Not supported	-0.21	-0.015
H8	IT competence -> Perceived ease of use	0.448	0.08	0.456	5.686***	Supported	0.286	0.595
H9	Self-efficacy -> Perceived ease of use	0.431	0.062	0.424	6.856***	Supported	0.311	0.552

Note: *** Significant at 1%, ** significant at 5%.

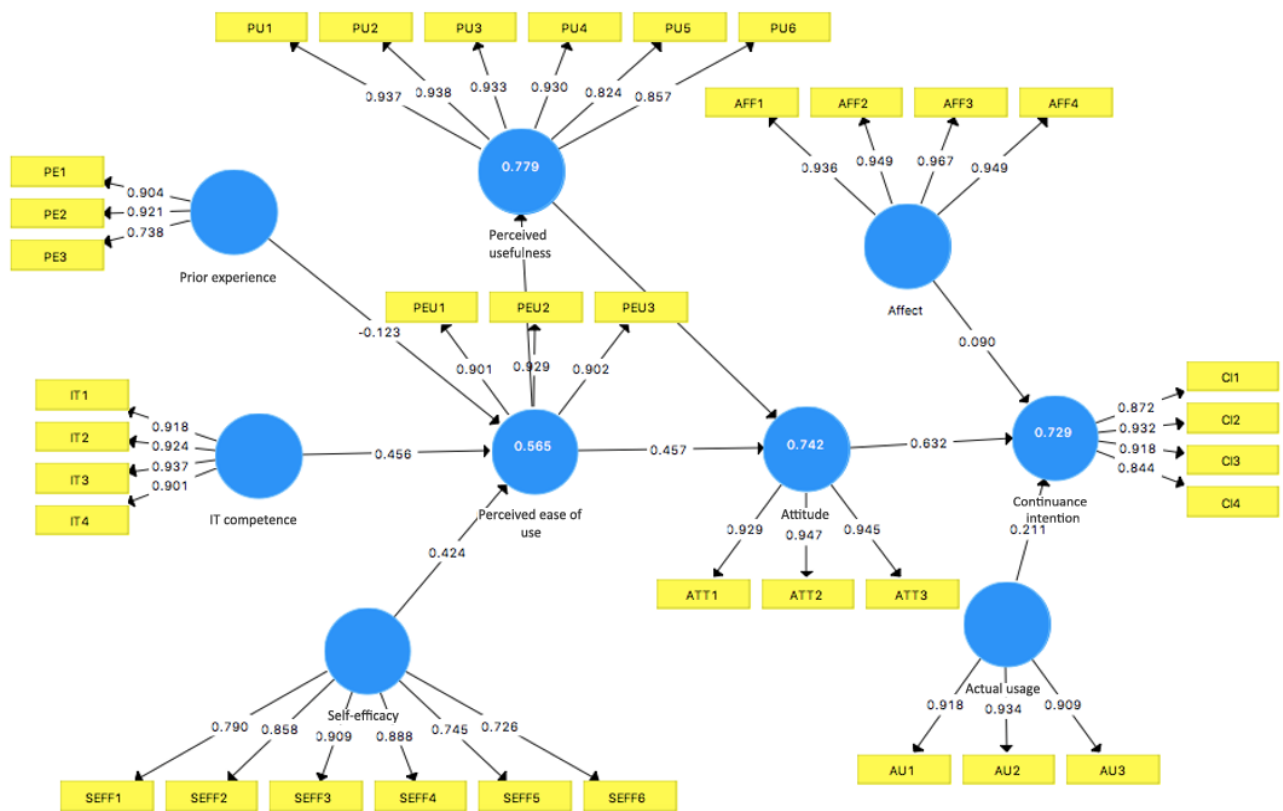


Figure 2.
PLS- path model.

The research model's predictive validity is demonstrated by using the variance explained (R^2) as the central criterion for assessing the structural model [36]. The results revealed that the study's main target construct (continuance intention) has a R^2 value of 72.4% while 'attitude' and 'perceived usefulness' account for 73.9% and 77.8% respectively. 'Perceived

ease of use' accounted for 55.7%. In other words, "perceived ease of use" was explained at 55.7% by antecedents. These values suggest good predictive and explanatory power for the model. The overall model fit was examined using the standardised root mean square residual (SRMR) composite factor model [35]. SRMR values less than 0.08 indicate a good model fit [37]. Since, the research model has an SRMR value of 0.061 which demonstrates good model fit.

Interestingly, affect was found not to have a significant effect on continuance intention ($\hat{\beta} = 0.90, p = 0.290$). Thus, rejecting H1 or H_a that affect has a positive effect on continuance intention. The alternative hypothesis (H_a) for H2 was significant ($\hat{\beta} = 0.632, p = 0.000$) and H_a for H3, with $\hat{\beta} = 0.211, p = 0.00$ which indicates that attitude and actual usage have a significant effect on students' continuance intentions.

The relationship between H_a perceived usefulness and attitude was significant $\hat{\beta} = 0.457, p = 0.00$. Perceived ease of use has an effect on attitude ($\hat{\beta} = 0.457, p = 0.000$) and perceived usefulness ($\hat{\beta} = 0.883, p = 0.000$), providing support for H5 and H6. However, the H_a of H7 has a positive effect on perceived ease of use was not supported even though the p -value shows significant value ($p = 0.012$). This is because the path coefficient was negative which was contrary to the H7; prior experience has a positive effect on perceived ease of use. On the other hand, H8 and H9 were found to be significant with $\hat{\beta} = 0.457, p = 0.000$ and $\hat{\beta} = 0.062, p = 0.000$ respectively.

6. Discussion

Many studies have adopted TAM to explain the acceptance of technologies and included additional predictors such as motivation and technology experience [14]. There are many benefits to online learning. The most outstanding is the learner's motivation to participate in the online learning process. This was proven in this study as perceived usefulness and attitude were the main predictors of students' continued intention to use MS Teams. The result of this study supports previous studies that indicate that attitude is one of the main predictors influencing the students' continued intention to use the technology along with perceived usefulness and perceived ease of use [14, 20, 38].

Interestingly, the prior experience did not have any significant effect on the perceived ease of use. Perhaps it was due to the fact that the platform itself was newly introduced to the students and they had the chance to have a long experience using it. Further investigation reveals that the students were having connection difficulties during their learning. According to Nguyen and Duong [39], the most significant issues with e-learning are internet access, learning equipment and other aspects that may influence students' perceived ease of use of the technology.

The affect factor in this study represents the emotional factor in terms of intrinsic motivation. We hypothesized that the affect factor would have a significant effect on the intention to continue learning through MS Teams but the actual result reveals that this is not the case. This study further supports Brazelton and Gorry [40] who indicate that learners might not participate even when technology is readily available for them.

It is interesting to note that affect positively influences the use of technologies in other research [14]. The students do not feel that they enjoyed using the technology due to the fact that MS Teams just introduced face-to-face lectures and limited interactions occur with the lecturer and their friends. According to Keller and Suzuki [41], in order to increase motivation, there needs to be more interaction online.

7. Conclusion

This study highlights that the continued usage of an online learning platform is not solely dependent on the technology itself. Instead, perceived usefulness, attitude and perceived ease of use are the main factors that impact students' intentions to continue using the platform. This finding emphasizes the importance of designing online learning platforms that are user-friendly, accessible and able to meet the needs of students in a way that is relevant to their learning experience.

The problem of newness and technological issues might frustrate students and hinder their motivation while using the platform. Therefore, it is crucial to provide students with adequate training and support for using the platform effectively.

Finally, the study suggests that more investigation is needed to understand the role of interaction between students and lecturers in promoting students' intrinsic motivation to use technology. This aspect is critical, especially in the online learning environment where a sense of connectedness and community is vital to maintaining students' engagement and motivation. Therefore, future studies should explore ways of enhancing the interaction between students and lecturers and evaluating its impact on students' learning outcomes and technology usage.

References

- [1] Z. Yu, "The effects of gender, educational level, and personality on online learning outcomes during the COVID-19 pandemic," *International Journal of Educational Technology in Higher Education*, vol. 18, p. 14, 2021. <https://doi.org/10.1186/s41239-021-00252-3>
- [2] G. Piccoli, "Web-based virtual learning environments: A research framework and a preliminary assessment of effectiveness in basic IT skills training," *MIS Quarterly*, vol. 25, no. 4, pp. 401-427, 2001. <https://doi.org/10.2307/3250989>
- [3] M. K. Lee, C. M. Cheung, and Z. Chen, "Acceptance of internet-based learning medium: The role of extrinsic and intrinsic motivation," *Information & Management*, vol. 42, no. 8, pp. 1095-1104, 2005. <https://doi.org/10.1016/j.im.2003.10.007>
- [4] R. Saadé and B. Bahli, "The impact of cognitive absorption on perceived usefulness and perceived ease of use in on-line learning: An extension of the technology acceptance model," *Information & Management*, vol. 42, no. 2, pp. 317-327, 2005. <https://doi.org/10.1016/j.im.2003.12.013>
- [5] Y. Lou, R. M. Bernard, and P. C. Abrami, "Media and pedagogy in undergraduate distance education: a theory-based meta-analysis of empirical literature," *Research & Development*, vol. 54, no. 2, pp. 141-176, 2006. <https://doi.org/10.1007/s11423-006-8252-x>

- [6] H.-J. So and T. A. Brush, "Student perceptions of collaborative learning, social presence and satisfaction in a blended learning environment: Relationships and critical factors," *Computers & Education*, vol. 51, no. 1, pp. 318-336, 2008. <https://doi.org/10.1016/j.compedu.2007.05.009>
- [7] R. M. R. Hussain, "E-learning in higher education institutions in Malaysia," *E-mento*, vol. 5, no. 7, pp. 72-75, 2004.
- [8] N. Duță and R. Foloștină, "Psycho-pedagogical training needs of university teaching staff—a comparative study," *Procedia-Social and Behavioral Sciences*, vol. 141, pp. 453-458, 2014. <https://doi.org/10.1016/j.sbspro.2014.05.079>
- [9] B. N. Yusuf and J. Ahmad, "Are we prepared enough? A case study of challenges in online learning in a private higher learning institution during the Covid-19 outbreaks," *Advances in Social Sciences Research Journal*, vol. 7, no. 5, pp. 205-212, 2020. <https://doi.org/10.14738/assrj.75.8211>
- [10] E. Chung, G. Subramaniam, and L. C. Dass, "Online learning readiness among university students in Malaysia amidst COVID-19," *Asian Journal of University Education*, vol. 16, no. 2, pp. 46-58, 2020. <https://doi.org/10.24191/ajue.v16i2.10294>
- [11] J. C. Roca, C.-M. Chiu, and F. J. Martínez, "Understanding e-learning continuance intention: An extension of the technology acceptance model," *International Journal of Human-Computer Studies*, vol. 64, no. 8, pp. 683-696, 2006. <https://doi.org/10.1016/j.ijhcs.2006.01.003>
- [12] J. C. Roca and M. Gagné, "Understanding e-learning continuance intention in the workplace: A self-determination theory perspective," *Computers in Human Behavior*, vol. 24, no. 4, pp. 1585-1604, 2008. <https://doi.org/10.1016/j.chb.2007.06.001>
- [13] M.-C. Lee, "Explaining and predicting users' continuance intention toward e-learning: An extension of the expectation–confirmation model," *Computers & Education*, vol. 54, no. 2, pp. 506-516, 2010. <https://doi.org/10.1016/j.compedu.2009.09.002>
- [14] H. Li and J. Yu, "Learners' continuance participation intention of collaborative group project in virtual learning environment: an extended TAM perspective," *Journal of Data, Information and Management*, vol. 2, pp. 39-53, 2020. <https://doi.org/10.1007/s42488-019-00017-8>
- [15] F. D. Davis, *A technology acceptance model for empirically testing new end-user information systems: Theory and results*. Massachusetts, United States: Sloan School of Management, Massachusetts Institute of Technology, 1986.
- [16] P. Lai, "The literature review of technology adoption models and theories for the novelty technology," *Journal of Information Systems and Technology Management*, vol. 14, no. 1, pp. 21-38, 2017. <https://doi.org/10.4301/s1807-17752017000100002>
- [17] B.-C. Lee, J.-O. Yoon, and I. Lee, "Learners' acceptance of e-learning in South Korea: Theories and results," *Computers & Education*, vol. 53, no. 4, pp. 1320-1329, 2009. <https://doi.org/10.1016/j.compedu.2009.06.014>
- [18] A. R. Alenezi, A. M. Abdul Karim, and A. Veloo, "An empirical investigation into the influence of image, subjective norm and self-identity on e-learning acceptance in Saudi government universities," presented at the Lifelong Learning International Conference 2010 (3LInC'10), 10 - 12 November, 2010, 2010.
- [19] M. J. Sanchez-Franco, "WebCT–The quasimoderating effect of perceived affective quality on an extending technology acceptance model," *Computers & Education*, vol. 54, no. 1, pp. 37-46, 2010. <https://doi.org/10.1016/j.compedu.2009.07.005>
- [20] R. H. Shroff, C. C. Deneen, and E. M. Ng, "Analysis of the technology acceptance model in examining students' behavioural intention to use an e-portfolio system," *Educational Technology*, vol. 27, no. 4, pp. 600-618, 2011. <https://doi.org/10.14742/ajet.940>
- [21] H.-P. Shih, "Extended technology acceptance model of internet utilization behavior," *Information & Management*, vol. 41, no. 6, pp. 719-729, 2004. <https://doi.org/10.1016/j.im.2003.08.009>
- [22] R. Arteaga Sánchez, A. Duarte Hueros, and M. García Ordaz, "E-learning and the University of Huelva: a study of WebCT and the technological acceptance model," *Campus-Wide Information Systems*, vol. 30, no. 2, pp. 135-160, 2013. <https://doi.org/10.1108/10650741311306318>
- [23] E. W. L. Cheng, S. K. W. Chu, and C. S. M. Ma, "Students' intentions to use PBWorks: A factor-based PLS-SEM approach," *Information and Learning Sciences*, vol. 120, no. 7/8, pp. 489-504, 2019. <https://doi.org/10.1108/ILS-05-2018-0043>
- [24] A. Singh, S. Sharma, and M. Paliwal, "Adoption intention and effectiveness of digital collaboration platforms for online learning: The Indian students' perspective," *Interactive Technology and Smart Education*, vol. 18, no. 4, pp. 493-514, 2021. <https://doi.org/10.1108/itse-05-2020-0070>
- [25] M. Bakhsh, A. Mahmood, and N. A. Sangi, "Examination of factors influencing students and faculty behavior towards m-learning acceptance: An empirical study," *International Journal of Information and Learning Technology*, vol. 34, no. 3, pp. 166-188, 2017. <https://doi.org/10.1108/ijilt-08-2016-0028>
- [26] H. Teck Soon and S. L. S.A. Kadir, "The drivers for cloud-based virtual learning environment: Examining the moderating effect of school category," *Internet Research*, vol. 27, no. 4, pp. 942-973, 2017. <https://doi.org/10.1108/intr-08-2016-0256>
- [27] T. Kim and G. Lee, "A modified and extended Triandis model for the enablers–process–outcomes relationship in hotel employees' knowledge sharing," *The Service Industries Journal*, vol. 32, no. 13, pp. 2059-2090, 2012.
- [28] J. F. Hair, G. T. M. Hult, C. M. Ringle, and M. Sarstedt, *A primer on partial least squares structural equation modeling (PLS-SEM)*, 2nd ed. Thousand Oaks, CA: Sage, 2016.
- [29] J. C. Westland, "Lower bounds on sample size in structural equation modeling," *Electronic Commerce Research and Applications*, vol. 9, no. 6, pp. 476-487, 2010. <https://doi.org/10.1016/j.elerap.2010.07.003>
- [30] U. Sekaran and R. Bougie, *Research methods for business: A skill-building approach*, 7th ed. West Sussex: Wiley & Sons, 2016.
- [31] J. C. Nunnally and I. H. Bernstein, "The assessment of reliability," *Psychometric Theory*, vol. 3, pp. 248-292, 1994.
- [32] C. Fornell and D. F. Larcker, "Evaluating structural equation models with unobservable variables and measurement error," *Journal of Marketing Research*, vol. 18, no. 1, pp. 39-50, 1981. <https://doi.org/10.2307/3151312>
- [33] R. P. Bagozzi and Y. Yi, "On the evaluation of structural equation models," *Journal of the Academy of Marketing Science*, vol. 16, no. 1, pp. 74-94, 1988.
- [34] J. Hair, W. Black, B. Babin, R. Anderson, and R. Tatham, *Multivariate data analysis*, 6th ed. Upper Saddle River, New Jersey: Pearson Prentice Hall, 2006.
- [35] J. Henseler, C. M. Ringle, and M. Sarstedt, "A new criterion for assessing discriminant validity in variance-based structural equation modeling," *Journal of the Academy of Marketing Science*, vol. 43, no. 1, pp. 115-135, 2015. <https://doi.org/10.1007/s11747-014-0403-8>

- [36] J. Henseler, M. R. Christian, and S. Marko, *Using partial least squares path modeling in advertising research: basic concepts and recent issues. Handbook of research on international advertising*. London: Edward Elgar Publishing, 2012.
- [37] L. T. Hu and P. M. Bentler, "Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives," *Structural Equation Modeling: A Multidisciplinary Journal*, vol. 6, no. 1, pp. 1-55, 1999. <https://doi.org/10.1080/10705519909540118>
- [38] A. Tamjidyamcholo, M. S. B. Baba, H. Tamjid, and R. Gholipour, "Information security–professional perceptions of knowledge-sharing intention under self-efficacy, trust, reciprocity, and shared-language," *Computers & Education*, vol. 68, no. 1, pp. 223-232, 2013. <https://doi.org/10.1016/j.compedu.2013.05.010>
- [39] H. U. N. Nguyen and L. N. T. Duong, "The challenges of e-learning through microsoft Teams for EFL students at van lang university in COVID-19," *AsiaCALL Online Journal*, vol. 12, no. 4, pp. 18-29, 2021.
- [40] J. Brazelton and G. A. Gorry, "Creating a knowledge-sharing community: If you build it, will they come?," *Communications of the ACM*, vol. 46, no. 2, pp. 23-25, 2003. <https://doi.org/10.1145/606272.606290>
- [41] J. Keller and K. Suzuki, "Learner motivation and e-learning design: A multinationally validated process," *Journal of Educational Media*, vol. 29, no. 3, pp. 229-239, 2004. <https://doi.org/10.1080/1358165042000283084>