ACCEPTANCE AND USE OF MASSIVE OPEN ONLINE COURSES: EXTENDING UTAUT2 WITH PERSONAL INNOVATIVENESS

Amillia Amid
Information Technology & Resources Module, Faculty of Education, Universiti Kebangsaan Malaysia, 43600 UKM Bangi, Selangor, MALAYSIA
amillia84.amid@gmail.com

Rosseni Din
STEM Enculturation Centre, Faculty of Education, Universiti Kebangsaan Malaysia, 43600 UKM Bangi, Selangor, MALAYSIA
rosseni@ukm.edu.my

ABSTRACT

Massive Open Online Courses (MOOCs) are online learning environment that have gained widespread acceptance, particularly in higher education institutions (HEIs). Because MOOCs can promote educational information, autonomous learning, and lifelong learning, they require continuous use. Although it is common to find studies on MOOCs in HEIs, research on the acceptance of MOOCs and use preferences among HEIs remains novel. Drawing on the Extended Unified Theory of Acceptance and Use of Technology (UTAUT2), the authors identify the factors that influence the acceptance and use of MOOCs among university students. Moreover, this article provides a significant theoretical contribution through the introduction of a new construct in the domain of information technology: personal innovativeness. Data was collected from 218 university students in Malaysia using purposive sampling and analyzed using Smart Partial Least Squares. The findings indicated that performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, habit, and personal innovativeness in the IT domain have a significant impact on MOOC acceptance and use among university students. This study contributes to a better understanding of how new technology is accepted and used such as MOOCs, as well as other forms of learning technology in HEIs.

Keywords: Massive Open Online Courses, acceptance and use, Extended Unified Theory of Acceptance and Use of Technology (UTAUT2), higher education, personal innovativeness (PI).

INTRODUCTION

Massive Open Online Courses (MOOCs) have a significant impact on the education field, particularly distance education. MOOCs are defined as online learning methods available to students around the world to improve their skills (Altalhi, 2020). They are different from traditional online courses as they possess unique characteristics such as immensity of scale, openness, and diversity (Tyler Sr., 2020; Lopes et al., 2014; Badi & Ali, 2016). MOOCs are open, large-scale, structured web-based courses that can be delivered by institutions of higher education (Deng, 2017) or taught for free over the Internet. Like any other online learning technology, MOOCs provide important benefits to students and learners. MOOCs also improve learning performance (Wang & Zhu, 2019). At present, a huge number of HEIs and universities make use of MOOCs. A MOOC is a suitable media for personalization of learning in the 21st century (Din, 2015). This is due to the nature of MOOCs. A MOOC is envisaged as a learning tool to give experience with tailored pedagogy, curriculum, media and environment to meet learners' different learning needs and aspirations that incorporates technology and the use of mobile devices to help all learners achieve optimum levels of learning beyond what could be imagined just a few decades ago (Din, 2015).

One critical issue to be addressed is how to ensure continuous use of MOOCs, rather than initial acceptance (Ouyang et al., 2017). Therefore, by considering the importance and demand for MOOCs among learners, several global universities have begun to deliver them through partnerships with MOOCs providers on their own websites (Pappano, 2012; Vardi, 2012). These MOOCs are available to any learner with Internet access – which is seen as a wise step to promote MOOCs globally. In addition, MOOCs can assist university graduates who lack job experience or skills by allowing them to enroll in online courses taught by experts and academics.

To cite this document:
Amid, A. & Din, R. (2021). Acceptance and use of massive open online courses: Extending UTAUT2 with personal innovativeness. *Journal of Personalized Learning*, *4*(1): 57-66.

Since 2008, the number of MOOCs has expanded rapidly. According to previous studies, more than 500 universities delivered more than 4200 MOOCs to 35 million students (Shah, 2017). Nevertheless, the completion rate of MOOCs has been questioned (less than 10%) and there is a consistently high dropout (or non-retention) of MOOC learners (Fianu et al., 2018; Hew et al., 2018; Ma & Lee, 2020). According to Rai and Chunrao (2016) and Chen (2017), approximately 7%–10% of learners complete the courses after signing up for MOOCs. In isolation, this figure appears to be enormous; however, when contrasted with the number of potential recipients of MOOCs, a few hundred million, it is clear there is an enormous gap. Thus, it is vital to understand what will inspire individual learners to accept and use MOOCs for learning in order to fill this gap. Recognizing the factors that influence the acceptance and use of MOOC is important for learners and it is also a major part of the process for MOOCs activities. Several studies have been conducted on MOOCs, with some focusing on learners' motivation for using them (Shrader et al, 2016), course completion (Chang et al., 2015), and the design of online learning materials for MOOCs. However, analyzing previous studies reveals that few research on MOOC acceptance and utilization have been done. By incorporating the personal innovativeness (PI) factor from the domain of information technology into the Extended Unified Theory of Acceptance and Use of Technology (UTAUT), the authors investigate which specific factors in the IT domain influence the acceptance and use of MOOCs among university students. The findings of this study are expected to provide a theoretical contribution to the body of knowledge in the IT domain. The several models and theories that have been used for the adoption of technology are discussed before the theoretical and conceptual framework are presented.

Theories and Models in Technology Adoption

Several models/theories related to technology adoption, with a new construct are described in this section. Among regularly utilized models are the Technology Acceptance Model (TAM), the Unified Theory of Acceptance and Use of Technology (UTAUT) and the Extended Theory of Acceptance and Use of Technology (UTAUT2).

A. Technology Acceptance Model (TAM)

The Technology Acceptance Model was developed by Davis (1989) to describe an individual's acceptance of information technology and is an extension of the Theory of Reasoned Action (TRA) (Venkatesh et al., 2003). The objective of TAM is to clarify determinants of computer acceptance among users. It replaces the 'attitude beliefs' construct in TRA with two new constructs: Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) to study attitudes towards use and Behavioral Intention (BI) to influence actual use. The degree to which a person believes that using a particular system would improve his or her work performance is referred to as PU, whereas the degree to which a person believes that using a particular system would be effort-free is referred to as PEOU (Cheah et al., 2011).

The TAM does not include the 'subjective norms' construct due to uncertainty of theoretical and psychometric status to parse the constructs (Davis, 1989). As the TAM evolved, new external constructs were introduced such as system quality, compatibility, computer anxiety, enjoyment, computing support, and experience (Davis, 1989). These constructs affected PU, PEOU, BI, and actual use or behavior. Although the TAM remains popular and has been applied in numerous studies on technology adoption, researchers have recently presented more theories that focus on organizational and consumer perspectives.

B. Unified Theory of Acceptance and Use of Technology (UTAUT)

The Unified Theory of Acceptance and Use of Technology (UTAUT) is an integrated model used to identify users' acceptance of technology (Venkatesh et al., 2003). UTAUT is a theory most frequently employed to explain technology acceptance in the education field and in business and information systems (Hamdan et al., 2015). Venkatesh et al. compared and tested constructs from eight different models of new technology adoption and utilisation. The following were the eight models and theories: (1) Theory of Reasoned Action (TRA), (2) Technology Acceptance Model (TAM), (3) Motivational Model (MM), (4) Theory of Planned Behavior (TPB), (5) Combined TAM and TPB (C-TAM-TPB), (6) Model of PC Utilization (MPCU), (7) Innovation Diffusion Theory (IDT), (8) Social Cognitive Theory. Venkatesh et al. (2003) then proposed UTAUT to explain technology acceptance and use of ICTs in the organizational field. The UTAUT focuses on four direct constructs (Performance Expectancy, Effort Expectancy, Facilitating Conditions, and Social Influence). Numerous studies have applied UTAUT to explain the acceptance and use of technology. A review of the literature reveals that these four constructs are significant indicators of the technology adoption (Huang

Journal of Personalized Learning, 4(1) 2021, 57-66.

& Kao, 2015; Decman, 2015; Tosuntas et al., 2015). The authors of the current study also explore whether the construct of behavioral intention affects the use of technology. Venkatesh et al. (2003) also identified an important role for several moderator constructs, namely (1) age, (2) gender, (3) experience, and (4) voluntary dependent on behavioral intentions and the use of technology.

C. Extended Unified Theory of Acceptance and Use of Technology (UTAUT2)

The UTAUT2 model is an improved version of UTAUT that explains the acceptance and use of technology among users. The UTAUT2 model evolved from the results generated using the UTAUT model. The UTAUT2 framework includes four constructs from the UTAUT model (performance expectancy, effort expectancy, facilitating conditions, and social influence) as well as three additional constructs (hedonic motivation, price value and habit) as precursors of behavioral intention and use behavior. Hedonic motivation is defined as the enjoyment or pleasure gained from employing a technology; price value is defined as the cognitive trade-off customers make between the perceived advantages of the applications and the monetary cost of utilizing them; and habit is defined as a perceptual construct that reflects the outcomes of previous experiences. In addition, the UTAUT2 model includes three moderating constructs: (1) age, (2) gender, and (3) experience (Venkatesh et al., 2012). Previous studies used the UTAUT2 in various technologies such as mobile technology (Baabdullah et al., 2014), phablets (Huang & Kao, 2015), mobile payments (Morosan & DeFranco, 2016), capture systems (Farooq et al., 2017) and online games (Xu, 2014). Social media and new technology, such as MOOCs, have a positive relationship with all of the constructs revealed in this theory (Huang, 2018). UTAUT2 is used in a few research in the education field, especially in the context of MOOCs. UTAUT2 is accepted as a valid framework for comprehending and investigating usage intentions within an educational setting (Prins, 2014). Therefore, the authors of this study examined factors that influence students' acceptance and utilization of MOOCs. Having reviewed the literature, the following hypotheses were developed for the study:

H1: Performance expectancy positively affects behavioral intention to use MOOCs

H2: Effort expectancy positively affects behavioral intention to use MOOCs

H3: Social influence positively affects behavioral intention to use MOOCs

H4: Facilitating conditions positively affects behavioral intention to use MOOCs

H5: Facilitating conditions positively affect use behavior towards MOOCs

H6: Hedonic motivation positively affects behavioral intention to use MOOCs

H7: Habit positively affects behavioral intention to use MOOCs

H8: Habit positively affects use behavior towards MOOCs

H9: Behavioral intention positively affects use behavior towards MOOCs

Journal of Personalized Learning, *4*(1) 2021, 57-66.

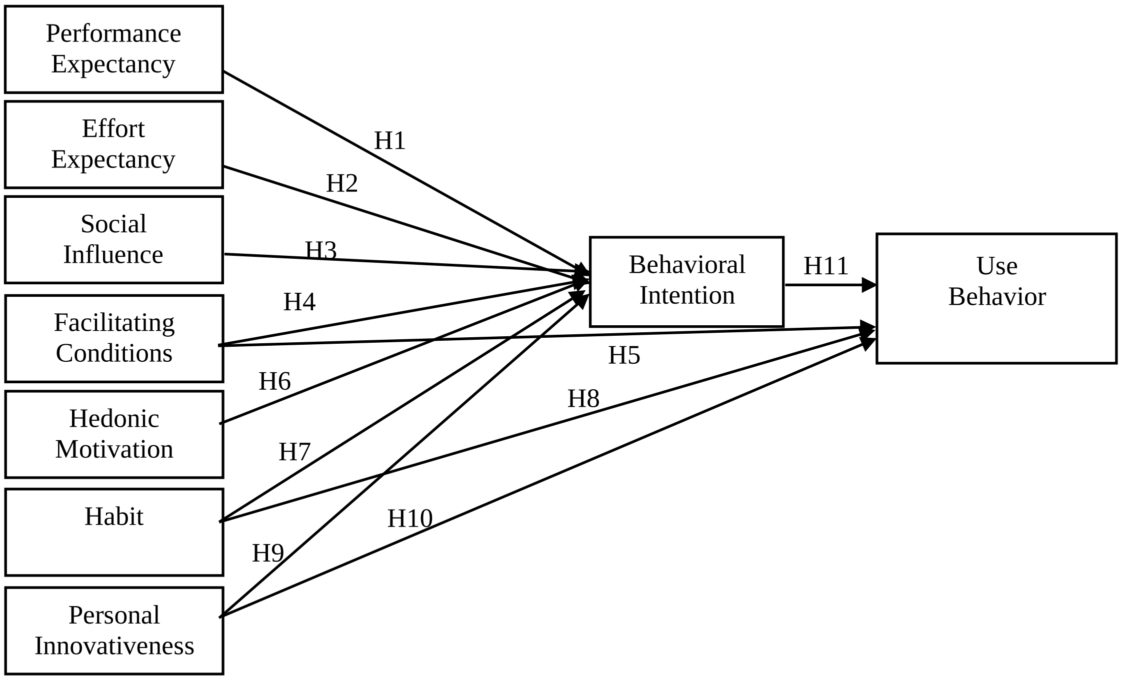

Figure 1. Proposed theoretical framework

D. Personal Innovativeness (PI) in the Domain of Information Technology

Agarwal and Prasad (1998) defined personal innovativeness (PI) as "the willingness of an individual to try out any new information technology". In the field of information technology (IT), the term PI also refers to a person's personal attitudes that reflect his or her tendency to experiment independently and apply new information technology developments (Raaij & Schepers, 2008). Thus, PI can be defined as the readiness to use the most recent innovative devices, or a risk-taking inclination associated with users' engagement with new advancements in the area of IT (Agarwali & Prasad, 1998). PI is an important construct for the study of individual behavior toward innovation, which is an old tradition in the study of innovation diffusion spread in general. PI suggested in this study differs from Rogers' (1995) "innovative" construct in Innovation Diffusion Theory, which measures the general reception of innovation when compared with others (Rogers, 1995). In this research, PI refers to the personal disposition of individuals who wish to attempt using new technologies in IT. Research has indicated that personal innovativeness (PI) is the personal factor that has the most influence on digital informal learning (He & Zhu, 2017). The following hypotheses were therefore developed:

H10: Personal innovativeness positively affects behavioral intention to use MOOCs

H11: Personal innovativeness positively affects use behavior towards MOOCs

METHODOLOGY

In this study, a quantitative technique was use to test the research hypotheses. The participants were chosen using a non-probability purposive selection approach. They were chosen from four public universities in the Klang Valley: UKM, UPM, UM, and UiTM Shah Alam. Participants were advised that participation was voluntary and were made aware that they would be asked to complete a questionnaire to assure the quality of the data. The questionnaire was only administered to participants upon the receipt of written consent. The questionnaire consisted of two sections. Questions in part A elicited demographic information such as gender, age, semester of study, university, and MOOC experience. Questions in part B contained questions on their acceptance and use of MOOCs.

Overall, 288 questionnaires were administered, of which 218 were returned and analysed. There was no missing data. The sample size was based on the analysis' force of power, based on the number of predictors (Hair et al., 2017; Ngah et al., 2020). Thus, this study's minimal sample size was 131, 80% power, with 13 predictors. Therefore, 218 respondents were selected in this study. The data was analyzed using Smart Partial

Journal of Personalized Learning, 4(1) 2021, 57-66.

Least Squares version 3.2.7, which employs confirmatory factor analysis (CFA). Items from Venkatesh et al. (2003) and Din (2018) were used, including performance expectancy, effort expectancy, social influence, facilitating conditions, and behavioral intention. Items including hedonic motivation, habit, and personal innovativeness were adopted from Venkatesh et al. (2012) and Farooq et al. (2017).

RESULTS AND FINDINGS

Respondents of the study were mostly between the ages of 23–34 years, as seen in the demographic profiles in Table 1, indicating that they were in the learner development phase. The respondents' gender ratio was imbalanced, with considerably more female respondents (165) than male respondents (53). One reason for this might be gender differences in the courses that were taken. Female students prefer courses that mostly provide MOOCs in their subject, such as art, literature, history, education, and foreign language, whereas male students tend to select science, technology, engineering, mechanics, and mathematics (Huang, 2018) courses. Regarding how long students had been using a MOOC for their subject, 14.7% of respondents had been using a MOOC since semester one, 6.9% since semester two, 21.6% since semester three, and 7.8% since semester four. In addition, 32.6% of respondents had been using a MOOC since semester five, 10.1% since semester six, and 6.4% since the final and seventh semester of their studies. There was a balanced proportion of respondents from all four universities in Malaysia (29.4% UKM, 23.4% UPM, 25.7% UiTM Shah Alam, and 21.6% UM).

The hypotheses were then tested using Smart PLS version 3.2.7. Smart PLS is a variance-based software that was utilized in this study to predict relationships between constructs. Because there was no expectation of getting a model fit by repeating the covariance matrix, variance-based software was ruled out for the study (Hair et al., 2017). The two steps in the analysis included the measurement model and the structural model.

Table 1: Respondent Profile

Construct	Category	Frequency	%
Gender	Male	53	24.3
	Female	165	75.7
Age	Less than 20	14	6.4
	20 – 24	192	88.1
	25 – 29	9	7.1
	30 – 34	3	1.4
Semester	1	32	14.7
	2	15	6.9
	3	47	21.6
	4	17	7.8
	5	71	32.6
	6	22	10.1
	7 and above	14	6.4
University	UKM	64	29.4
	UPM	51	23.4
	UiTM Shah Alam	56	25.7
	UM	47	21.6
Experience	Less than 1 year	123	56.4
	1 – 3 years	88	40.4
	4 – 6 years	7	3.2
Total		218	100

Journal of Personalized Learning, 4(1) 2021, 57-66.

A. Measurement Model

The outer model (Hair et al., 2017) is another name for the measurement model. In the theoretical framework, the measurement model was used to determine the validity of the item and construct relationship. The measuring model included both convergent and discriminant validity. According to Hair et al. (2014), convergent validity is obtained when Cronbach's alpha is ≥ 0.7, the Composite Reliability (CR) is ≥ 0.7 and the average variance explained (AVE) is ≥ 0.5. Table 2 shows the complete list of convergent validity outcomes. Discriminant validity, the second type of validity, reveals that the construct is distinct from other theoretical constructs and examines how much each indicator represent a construct. To confirm that the constructs are statistically unique and distinct from other constructs, an appropriate assessment of discriminant validity is required. As proposed by Henseler et al. (2015), the HTMT ratio is employed as a measure of discriminant validity. As a general rule, if the HTMT value is larger than 0.85, there is a probable discriminant validity concern (Hair et al., 2017). Table 3 indicates that discriminant validity in the present study is less than 0.85, 0.90 and 1.00. Table 3 shows that the study had discriminant validity because all HTMT values were lower than the value given by Franke and Sarstedt (2019).

B. Structural Model

As previously indicated, the data was analyzed using variance-based partial least square (PLS) structural equation modelling (SEM). Calculations were performed using Smart-PLS-3.2.7. To get the path coefficient (beta) values, all hypothesized path relations were run through the structural model, and t-values analysis was also used to determine the significance of the relationships. As suggested by Hair et al. (2017), the bootstrapping technique was used to test the hypotheses. Of the 11 hypotheses, only one was unsupported, as indicated in Table 4. Specifically, performance expectancy was found to be contributing positively to behavioral intention (ß = 0.097, t = 2.081, P < 0.05), effort expectancy was found to be contributing positively to behavioral intention (ß =0.119, t = 2.748, P < 0.05), and social influence was found to be contributing positively to behavioral intention (ß =0.220, t = 4.723, P < 0.05). However, facilitating conditions was not positively contributing to behavioral intention (ß = -0.093, t = 1.626, P < 0.05). Additionally, facilitating conditions was found to be contributing positively to use behavior (ß = -0.122, t = 1.953, P < 0.05), hedonic motivation was found to be contributing positively to behavioral intention (ß = 0.293, t = 4.742, P < 0.05), habit was found to be contributing positively to behavioral intention (ß = 0.197, t = 3.175, P < 0.05), and habit was found to be contributing positively to use behavior (ß = 0.190, t = 2.648, P < 0.05).

The construct of personal innovativeness was found to be contributing positively to behavioral intention (ß = 0.313, t = 4.876, P < 0.05) and use behavior (ß =0.198, t = 2.535, P < 0.05) while behavioral intention was found to be contributing positively to use behavior (ß =0.367, t = 4.623, P < 0.05). Thus, only H4 was not supported as facilitating conditions was found to have a negative contribution towards behavioral intention to use MOOCs. Hypotheses H1, H2, H3, H5, H6, H7, H8, H9, H10 and H11 were all supported. The findings confirmed past studies by Huang (2018) and Franke and Sarstedt (2019) for performance expectancy, effort expectancy, social influence, and facilitating conditions, as well as by Gibson (2019) for hedonic motivation and habit. Although previous studies have found facilitating conditions to have a positive relationship with behavioral intention (Arain et al., 2019), the current study revealed the opposite. Nevertheless, this finding aligns with those from Venkatesh et al. (2012) and Gibson (2019). The authors also found that personal innovativeness (PI) has a positive relationship with university students' acceptance and utilization of MOOCs. These findings are in line with those from Tseng et al. (2019) and Gunasinghe et al. (2018).

Journal of Personalized Learning, *4*(1) 2021, 57-66.

Table 2: Convergent Validity

Construct	AVE	Cronbach's Alpha	Composite Reliability
Performance Expectancy (PE)	0.765	0.709	0.867
Effort Expectancy (EE)	0.607	0.792	0.861
Social Influence (SI)	0.718	0.804	0.884
Facilitating Conditions (FC)	0.648	0.821	0.880
Hedonic Motivation (HM)	0.852	0.913	0.945
Habit (H)	0.732	0.877	0.916
Personal Innovativeness (PI)	0.601	0.772	0.856
Behavioral Intention (BI)	0.644	0.724	0.844
Use behavior (UB)*	1.000	1.000	1.000

* Single Item construct

Table 3: Discriminant Validity HTMT

Construct	BI	EE	FC	H	HM	PE	PI	SI	USE
BI									
EE	0.327								
FC	0.553	0.519							
H	0.624	0.428	0.578						
HM	0.750	0.466	0.733	0.585					
PE	0.496	0.632	0.551	0.551	0.578				
PI	0.374	0.351	0.453	0.637	0.438	0.328			
SI	0.595	0.543	0.591	0.626	0.677	0.559	0.472		
USE	0.376	0.136	0.193	0.364	0.143	0.196	0.146	0.216	

Table 4: Structural Model/ Hypothesis Testing

Hypothesis	Relationship	Beta	Error	T value	P Values	Decision	VIF
H1	PE→BI	0.097	0.046	2.081	0.019	Supported	1.451
H2	EE→BI	0.119	0.043	2.748	0.003	Supported	1.538
H3	SI→BI	0.220	0.046	4.723	0.000	Supported	1.740
H4	FC→BI	-0.093	0.057	1.626	0.052	Unsupported	1.835
H5	FC→USE	-0.122	0.062	1.953	0.025	Supported	1.319
H6	HM→BI	0.293	0.062	4.742	0.000	Supported	2.028
H7	H→BI	0.197	0.062	3.175	0.001	Supported	1.925
H8	H→USE	0.190	0.072	2.648	0.004	Supported	2.009
H9	PI→BI	0.313	0.064	4.876	0.000	Supported	1.912
H10	PI→USE	0.198	0.078	2.535	0.006	Supported	2.105
H11	BI→USE	0.367	0.079	4.623	0.000	Supported	2.413

DISCUSSION

The findings of this study showed the effects of performance expectancy, effort expectancy, facilitating conditions, social influence, hedonic motivation, habit, and personal innovativeness on behavioral intention. In addition, the study examined how this behavioral intention can predict MOOC usage. The findings indicated that behavioral intention influenced performance expectancy and effort expectancy. This result is in line with Venkatesh et al. (2012). Social influence appears to have a significant contribution on behavioral intention, which is also consistent with previous studies. However, facilitating conditions were identified in UTAUT2 as having both a direct and indirect impact on behavioral intention. Nonetheless, the indirect impact through behavioral intention is not supported by this study. To find the source of this problem, more investigation is required. One reason might be that students use MOOCs for academic purposes only. Alternatively, it might be that students did not expect more support from their respective universities regarding the technology. The findings also indicated that facilitating conditions has a negative relationship with behavioral intention. Hedonic motivation and habit, two new constructs added by Venkatesh et al. (2012) in the UTAUT2 model, had a significant impact on behavioral intention to use MOOC. Personal innovativeness was also significant. This finding is consistent with past studies (Gunasinghe et al., 2018; Dhiman et al., 2019).

CONCLUSION

Based on UTAUT2, this study presented findings on university students' acceptance and use of MOOCs, as well as introducing and verifying a new construct's function and personal innovativeness (PI). This study contributes to the general body of knowledge by making a theoretical contribution. The findings indicate that all UTAUT2 constructs, and PI in the IT domain have a positive relationship with university students' acceptance and use of MOOCs. Furthermore, performance expectancy, effort expectancy, facilitating conditions, social influence, hedonic motivation, habit, and personal innovativeness are UTAUT2 constructs that have a significant role in MOOC adoption and use. This study paves the way for future research in various settings to evaluate the role of personal innovativeness in influencing technology acceptance and use.

Acknowledgment

We would like to convey our utmost appreciation to the STEM Enculturation Research Centre, Faculty of Education, Universiti Kebangsaan Malaysia for their support to publish this work using the STEM & Minda Grant GG-2021-002.

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