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Research Article

Examining Teachers' Behavioral Intention to Use E-learning in Teaching of Mathematics: An Extended TAM Model

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Abstract

The aim of this study was to examine factors that influenced experienced teachers' intention to use E-learning in their teaching of mathematics. Data were collected using a questionnaire from 161 secondary school mathematics teachers who completed a six-month in-service online training provided by the Indonesian Ministry of Education. The Technology Acceptance Model (TAM) was used as the framework while E-learning experience was included as an additional construct. An extended TAM model was proposed and tested in this study. It consisted of five constructs, namely: intention to use, perceived usefulness, perceived ease of use, attitude toward using, and experience. Data were analyzed using Structural Equation Modelling with SMARTPLS 3.0. The findings showed that attitude toward E-learning use and E-learning experience were the two most significant constructs in predicting E-learning use. Contrary to previous studies, perceived ease of use and perceived usefulness were non-significant factors for the prediction of the behavioral intention. Implications for future research and practices are discussed.

Keywords: behavioral intention, teachers' intention to use e-learning, extended TAM model, teachers' e-learning experience, e-learning in mathematics classroom

INTRODUCTION

In Indonesia, 45.5 million school students and 3.1 million teachers are dependent on online teaching and learning due to school closures during COVID-19 pandemic (Mailizar, Almanthari, Maulina, & Bruce, 2020). As a result, education in the country has changed dramatically with the rising need of E-learning adoption. According to Cigdem and Topcu (2015), institutions that expect their teaching staff to use E-learning should consider their behavioral intention to use E-learning systems. The Technology Acceptance Model (TAM) (Davis, 1986) is the mostly used model in studies of users' acceptance of technologies (Cigdem & Topcu, 2015). The main aim of the model is to describe users' behavior toward the adoption of technology (Chang, Hajiyev, & Su, 2017).

TAM has been widely used in studies that investigate e-learning. Although the model has been scrutinized, validated and praised for its contribution to science, it has been argued that it has some limitations.

Theoretically, some researchers have argued that the popularity of TAM is linked to its simplicity which does not address the complexity associated with e-learning use in institutional contexts (Ajibade, 2018; Chuttur, 2009). However, the core of the theory remains the same in most studies and the majority of changes are made to the external variables discussed in the theory or adding elements as part of perceived usefulness and perceived ease of use. For example, Venkatesh and Davis (2000) proposed TAM 2 with additional variables with additional constructs. Some of the constructs broke PU into several components such as job relevance, result demonstrability, etc. Another limitation of TAM is that studies that follow it depend mainly on self-reported data without use of data generated from systems about their use (Chuttur, 2009). Ajibade (2018) argues that TAM assumes that more use is better without placing adequate emphasis on impact of system use on performance. Ajibade (2018) also argues that TAM is more appropriate for personal use than institutional use due its lack of focus on the impact on policies, management, expectations and workplace factors. However, TAM has been adapted differently to suit the specific requirements for specific institutions and contexts.

Previous studies have extended the TAM model, resulting in various external factors of TAM (Abdullah & Ward, 2016; Martin, 2012). Abdullah and Ward (2016) conducted a meta-analysis study and found that subjective norm, experience, perceived enjoyment, computer anxiety and self-efficacy were the most commonly used external factors for TAM. According to Abdullah and Ward (2016), experience is one of the most commonly used external factors in E-learning acceptance studies.

As discussed earlier, TAM was adapted differently by different researchers based on several factors including their needs, contexts, research focus and conceptualization of the TAM. In this study, experience was included due to the need to examine teachers' prior e-learning experience on their perceived usefulness, perceived ease of use and behavioral intention. As discussed in this study, there is dearth of research in this area and investigating it contributes to our understanding of its importance and impact.

The previous studies that used experience as an external factor of TAM looked at different types of E-learning users namely, employees (Lee, Hsieh, & Chen, 2013; Lee, Hsieh, & Ma, 2011; Purnomo & Lee, 2013), students (Abbad, Morris, & De Nahlik, 2009; Lau & Woods, 2008; Williams & Williams, 2010), student and educators (Martin, 2012), and teachers (De Smet, Bourgonjon, De Wever, Schellens, & Valcke, 2012).

In terms of teachers' experience in E-learning, many teachers in Indonesia have experiences of using E-learning for their professional development (PD). The Ministry of Education and Culture offers a six-month online PD course for teachers in 42 higher education institutions throughout the country (Mailizar, Samingan, Rusman, Huda, & Yulisman, 2020). This course, consisting of general pedagogy, subject-specific pedagogy, and content area, is a 12-credit raining course required for teachers in order to be awarded a teaching certificate.

However, to the best of our knowledge, no empirical studies were conducted about secondary school teachers' behavioral intention to use E-learning in teaching, particularly that focus on secondary mathematics school teachers who have experience in using E-learning for their PD (hereafter, *experienced teachers*). Therefore, in this study, teachers' E-learning experience during their PD was used as an external factor of TAM model. Consequently, using TAM as a theoretical foundation and employing Structural Equation Modelling (SEM), this study aims to examine factors affecting experienced teachers' behavioral intentions to use E-learning in their teaching of mathematics.

THEORY AND RELATED LITERATURE

Several models, such as Technology Acceptance Model (TAM) (Davis, 1986), Theory of Planned Behavior (TPB) (Ajzen, 1991), and Unified Theory of Acceptance and Use of Technology (Venkatesh, Morris, Davis, & Davis, 2003) have been developed and proposed to investigate users' intention to use emerging technology. TAM is one of the most widely used models to investigate and predict users' technology acceptance.

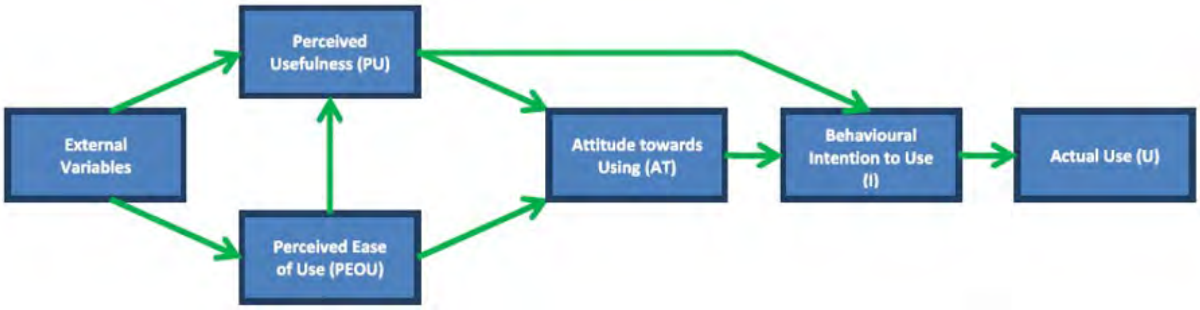

Figure 1. Technology acceptance model (Davis, 1986)

Technology Acceptance Model

TAM is based on the Theory of Reasoned Action proposed by Fishbein and Ajzen (1975). According to Fishbein and Ajzen, behaviour is determined by attitude and subjective norm. Attitude refers to the positive or negative feelings about the behaviour and the subjective norm refers to a person's circle of important people and their acceptance of performing the behaviour.

According to Davis (1996), TAM (**Figure 1**) is a framework used to investigate how and when users adopt emerging technology. TAM has been proved efficient in explaining users' behavior to use computing technology (Teo, 2010). This model shows the relationship among perceived ease of use (PEU), perceived usefulness (PU), attitude toward use (AT), and intention to use technology (BI).

According to Davis (1989), behavioral intention is affected by attitude toward use. It is also directly and indirectly affected by perceived ease of use and perceived usefulness. Furthermore, perceived ease of use has a direct effect on perceived usefulness, yet the reverse is not true.

Intention to use has a close link with actual behavior (Kiraz & Ozdemir, 2006). It is a factor that shows users' willingness to perform a behavior (Ajzen, 1991). According to Teo (2010), using intention to use as a dependent variable has advantages since asking participants about their actual use of E-learning may discourage them to participate in a study. In addition, compared to actual use, behavioral intention to use is a more progressive dependent variable. Therefore, the present study employed intention to use as a dependent variable.

TAM has been widely used around the globe to examine secondary teacher acceptance of e-learning. For instance, De Smet et al. (2012) collected data from 505 Flemish secondary school teacher to understand acceptance of e-learning by secondary school teachers and to investigate the instructional use of e-learning. The study indicated that perceived ease of use of e-learning is the strongest predictor in e-learning acceptance. Another study was conducted by (Alzahrani, 2019) in Saudi Arabia. This study revealed that the TAM model can be used to explain factors influencing secondary school teachers` acceptance of e-learning in context of Saudi Arabia. Stockless (2018) conducted a study in Canada aiming at identifying the factors that influence teachers' intention to use e-learning. This study showed that perceived usefulness is a strong predictor or teachers' intention to use e-learning.

The TAM Variables and Hypotheses

Experience as an external variable of TAM

Existing studies have revealed that experience significantly influences users' perceived ease of use (PEU) of E-learning systems (De Smet et al., 2012; Lee et al., 2013; Purnomo & Lee, 2013). Users who have more experience tend to have a more favorable feeling toward technology ease of use (Lee et al., 2013; Purnomo & Lee, 2013). Regarding perceived usefulness (PU), prior studies have revealed a significant effect of users' experience on their PU of E-learning (Lee et al., 2013; Martin, 2012; Purnomo & Lee, 2013; Rezaei, Mohammadi, Asadi, & Kalantary, 2008). In terms of behavioral intention, previous studies have also shown that users' computer experience affects their intention to use E-learning technology (De Smet et al., 2012;

Premchaiswadi, Porouhan, & Premchaiswadi, 2012; Williams & Williams, 2010). In this current study, we used teachers' E-learning experience during their in-service professional development program (hereafter *XIT*) as an external variable of TAM. Hence, we proposed the following hypotheses:

H1. XIT significantly affects PU of E-learning in teaching of mathematics

H2. XIT significantly affects PEU of E-learning in teaching of mathematics

H3. XIT significantly affects BI to use E-learning in teaching of mathematics

Perceived ease of use (PEU)

In the context of E-learning, PEU is defined as the extent to which a user believes that using E-learning will be free of effort (Lin, Chen, & Fang, 2010). It has an effect on PU (Davis, 1989) as well as on AT (Chang, Yan, & Tseng, 2012; Wu & Zhang, 2014). Furthermore, numerous studies have validated the significance of PEU as one of the main predictors of attitude toward acceptance of technology (Briz-Ponce & García-Peñalvo, 2015; Calisir, Altin Gumussoy, Bayraktaroglu, & Karaali, 2014; Hamid, Razak, Bakar, & Abdullah, 2016). In this study, we looked at teachers' PEU of E-learning in teaching. Hence, the following hypotheses were proposed.

H4. PEU significantly affects PU of E-learning in teaching of mathematics

H5. PEU significantly affects AT toward using E-learning in teaching of mathematics

H6. PEU significantly affects BI to use E-learning in teaching of mathematics

Perceived usefulness (PU)

Lin et al. (2010) define PU of E-learning as the extent to which a user believes that E-learning can help them to achieve learning objectives. Previous studies showed that PU is one of the main factors that influences users' attitude toward technology (Chang et al., 2012; Hamid et al., 2016; Hess, McNab, & Basoglu, 2014; Mou, Shin, & Cohen, 2017). Furthermore, PU also has a direct and an indirect effect on behavioral intention (Teo, 2010; Wong, 2015). Hence, regarding the previous studies, we proposed two hypotheses:

H7. PU significantly affects BI to use E-learning in teaching of mathematics

H8. PU significantly affects AT toward using E-learning in teaching of mathematics

Attitude toward using (AT)

Kaplan (1972) defined attitude as a tendency in response to an event in a favorable or an unfavorable way. Many studies on E-learning acceptance have showed that attitude becomes a significant predictor of BI to use E-learning (e.g., Cheung & Vogel, 2013; Tosuntaş, Karadağ, & Orhan, 2015). The connection between AT and BI implied that users tend to follow certain behaviors based on their positive attitude toward them (Keong, Albadry, & Raad, 2014). Furthermore, attitude toward technology fully mediates effects on behavioral intention. Therefore, we proposed hypothesis 9.

H9. AT significantly affects BI to use E-learning in teaching of mathematics

Behavioral intention (BI)

There are two outcome variables of the TAM model, namely behavioral intention (BI) and actual use (AU). BI is defined as behavioral tendency to keep using technology in the future; therefore, it determines acceptance of technology (Alharbi & Drew, 2014). Previous studies have confirmed that BI positively affects AU. Furthermore, earlier studies showed that BI is influenced by PU (Tarhini, Elyas, Akour, & Al-Salti, 2016), PEU (Tarhini et al., 2016; Wu & Zhang, 2014), and AT (Hussein, 2017; Letchumanan & Tarmizi, 2011; Sharma & Chandel, 2013; Taat & Francis, 2019). As mentioned previously, in this study, BI is a dependent variable. Therefore, we incorporated intention to use E-learning as an outcome of our research model as presented in **Figure 2**.

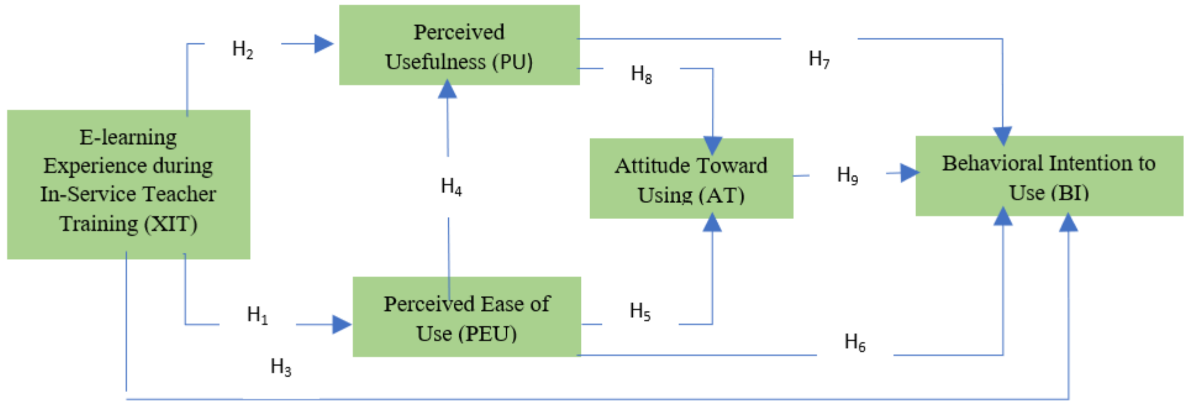

Figure 2. The structural model of the hypotheses

RESEARCH MODEL

The discussion presented previously suggests that E-learning experience is a significant factor that strongly affects PEU, PU and BI in the E-learning context. As mentioned earlier, in the present study, teachers' E-learning experience during their in-service training was included as an external factor of the TAM model, as shown in **Figure 2**.

METHOD

Design of the Study

We employed a quantitative approach with a cross-sectional questionnaire (Fraenkel, Wallen, & Hyun, 2011). A quantitative method is able to provide reliable, valid, objective and generalizable findings, and questionnaires can be distributed to many participants. Furthermore, according to Fraenkel et al. (2011), a quantitative method enables generalizations about the whole population. In addition , a quantitative study relies on hypothesis testing, where clear guidelines and objectives can be followed (Shank & Brown, 2013). In this research, we tested hypotheses to predict secondary school teachers' behavioral intention to use E-learning in their teaching of mathematics.

Instrument Design and Development

According to Lew, Lau, and Leow (2019), questionnaire is a widely used method in studies of technology acceptance. It allows researchers to collect data that reflect opinions and behaviors of a group of people (Queirós, Faria, & Almeida, 2017). Therefore, a questionnaire of 21 Likert-scale items was developed. The question items were designed based on the five constructs (PU, PEU, AT, BI, and XIT) of the model. We labelled the five scale questions as 'Strongly Disagree', 'Disagree', 'Neutral', 'Agree, and 'Strongly Agree', and they were ranged from 1 to 5, respectively.

In order to assess content validity of the constructs, the questionnaire was reviewed by two experts. The instrument was examined through content validity index. The experts were requested to examine if the items covered all related aspect. The results showed that the average score of the item above the threshold value which is 0.800 (Halek, Holle, & Bartholomeyczik, 2017). Furthermore, all items values were above the threshold values of 0.780. Furthermore, a pilot test was carried out with eight selected teachers. After the teachers completed the questionnaire, they were interviewed to make sure that they understood the questions and that questionnaire items made sense for them. The questions were then revised according to comments from the interviewees.

Table 1. Demographic profile of respondents

Demographic Background		Number of Participants	Percentage
Gender	Male	83	51.6 %
	Female	78	48.4 %
Level of Education	Undergraduate Degree	141	87.6 %
	Postgraduate Degree	20	12.4 %
Teaching Experience	0-5 Years	32	19.9 %
	6-10 Years	58	36.0 %
	11-15 Years	48	29.8 %
	16-20 Years	14	8.7 %
	More than 20 Years	9	5.6 %
Teacher Certification	Yes	117	72.7 %
	No	44	27.3 %

Research Participants

The respondents of this study were secondary school mathematics teachers in Indonesia who participated in an in-service professional development program offered by the government through an online learning system. It took six months for participants to complete the training. The contents of training were contents of mathematics and the subject specific pedagogy. The training has been offered since 2018 and is available at 42 Higher Education Institutions (HEIs) across the nation.

The study was conducted in one of the assigned HEIs that provided the training for 1200 teachers in 2019 consisting of five cohorts. The institution is a public university located in northern end of Sumatra island, Indonesia. This university is ranked in the top 20 Universities in the country. We chose this university as the teachers who participated in the teacher professional development were not only from the province where the university located but also from other provinces in Indonesia. The participants of the training program were enrolled by the ministry of education and culture into the university.

Random sampling was employed for the selection of respondents. Participants' demographic information is highlighted in **Table 1**.

A total of 161 secondary school mathematics teachers in Indonesia participated in this study by completing the questionnaire. Respondents consisted of 83 (51.6%) male and 78 (48.4%) female teachers. The majority of respondents had an undergraduate degree (87.6%), while the remaining had a postgraduate degree (12.4%). Majority of the participants had more than six years of teaching experience as well as were being certificated by the Indonesian government.

Data Collection

Prior to data collection, we acquired ethical approval for this study. Subsequently, we conducted an online questionnaire because it could be easily administered and accessible with various devices (See., Fraenkel et al., 2011). The majority of participants were contacted through WhatsApp and email. We administered the online questionnaire in Google Form by sending a link to participants and keeping the questionnaire active for four weeks.

Data Analysis

Structural Equation Modelling (SEM) was utilized. Partial Least Squares SEM (PLS-SEM) was appropriate for the study in order to predict teachers' behavioral intention to use E-learning for teaching of mathematics. Therefore, SMART PLS 3.0 was run to examine Confirmatory Factor Analysis (CFA) and to assess the reliability, validity, internal consistency of the model. A structural model was developed, and the hypotheses were confirmed.

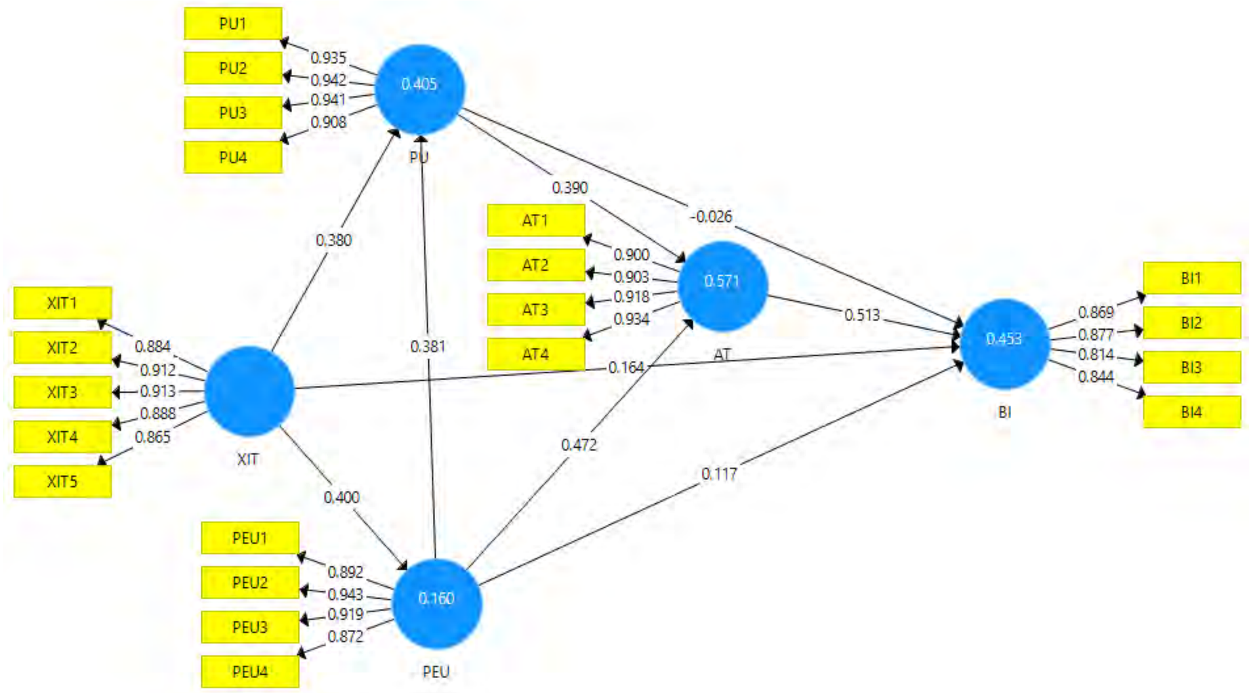

Figure 3. Structural model and path coefficients

RESULTS

Factor Analysis

Five constructs, namely, XIT, PEU, PU, AT, and BI had been revealed for assessing factor analysis. We present the structural model and its path coefficients in **Figure 3**.

To assess the accuracy of the structural model, we measured R^2 values. The structural model shows that R^2 is 0.453 for BI as an endogenous construct. It implies that the four exogenous constructs (XIT, PEU, PU and AT) moderately explain 45.3% of the variance in CI (Hair, Hult, Ringle, & Sarstedt, 2017). The inner model suggests that AT is the strongest predictor that significantly affects BI (β= 0.513, t-value = 5.880), followed by XIT (β= 0.164, t-value = 2.267). The results indicate that AT and XIT have a strong positive relationship with BI by having t-value > 1.645 for a significance level of 5% (α = 0.05) (Hair et al., 2017).

Regarding AT as an endogenous construct, the model shows that R^2 is 0.571 for AT. This indicates that the two constructs (PEU and PU) moderately explain 57.1 % of the variance in AT. The model also suggests that PEU is the strongest factor that significantly affects AT (β= 0.472, t-value = 6.217), followed by PU (β= 0.390, t-value = 5.771). Having those t values, it indicates that PEU and PU have a strong positive relationship with AT.

In addition, in terms of PU, the results reveal that R^2 is 0.405 for PU. This implies the two constructs (PEU and XIT) moderately explain 40.5% of the variance in PU. The model shows that PEU is the strongest predictor that significantly affects PU (β= 0.381, t-value = 5.369), followed by XIT (β= 0.380, t-value = 5.971). These results indicate that XIT and PEU have strong positive relations.

Furthermore, three assessment criteria namely, convergent validity, internal consistency reliability, and discriminant validity were employed to assess the theoretical model. Regarding convergent validity, we measured the outer loadings of the indicators and the Averaged Variance Extracted (AVE) (Hair et al., 2017). Loading values equal to or larger than 0.7 indicate adequate convergent validity (Hair et al., 2017). In terms of Composite Reliability (CR), which measures internal consistency reliability, CR value above 0.7 is regarded as adequate. **Table 3** presents loading values, CR and AVE of the constructs.

Table 2. Convergent validity and composite reliability

Construct	Items	Loadings	CR	AVE
PU	PU1	0.935	0.900	0.867
	PU2	0.942		
	PU3	0.941		
	PU4	0.908		
PEU	PEU1	0.892	0.755	0.614
	PEU2	0.943		
	PEU3	0.919		
	PEU4	0.872		
AT	AT1	0.900	0.889	0.835
	AT2	0.903		
	AT3	0.918		
	AT4	0.934		
BI	BI1	0.869	0.847	0.725
	BI2	0.877		
	BI3	0.814		
	BI4	0.844		
XIT	XIT1	0.884	0.951	0.797
	XIT 2	0.912		
	XIT 3	0.913		
	XIT 4	0.888		
	XIT 5	0.865		

Table 3. Discriminant validity (Fornell-Lacker criterion)

	AT	BI	PEU	PU	XIT
AT	**0.914**				
BI	0.650	**0.851**			
PEU	0.681	0.518	**0.907**		
PU	0.641	0.453	0.532	**0.932**	
XIT	0.449	0.428	0.400	0.532	**0.892**

Table 2 shows that all indicators have loadings over 0.7, which is considered a high convergent validity and acceptable (Hair et al., 2017). It implies that all indicators have exceeded the threshold value; therefore, indicator reliability was satisfactory. Furthermore, values of AVEs satisfy the threshold level of AVE (≥ 0.5), indicating that convergent validity is confirmed (Hair et al., 2017). Therefore, we can conclude that the constructs meet reliability and convergent validity requirements.

Furthermore, we employed cross-loading criterion (Hair et al., 2017) and Heterotrait-Monotrait Ratio of Correlation (HTMT) (Henseler, Ringle, & Sarstedt, 2015) to assess discriminant validity. Constructs exhibit threshold of discriminant validity when the square roots of AVEs are all higher than the value of inter-construct on the same columns and rows (Fornell & Larcker, 1981). **Table 4** shows that all constructs have met the threshold of discriminant validity for AT (0.914), BI (0.851), PEU (0.907), PU (0.932) and XIT (0.892).

Regarding cross-loading criterion, **Table 4** shows that the loading values of all indicators on the constructs were all higher than the loading values of other constructs. This indicates that the indicators of the constructs are interchangeable.

As mentioned earlier, we measured Heterotrait-Monotrait Ratio of Correlation (HTMT) (Henseler (2010) as an alternative approach to assess discriminant validity. HTMT was employed to confirm every construct is distinct from one another. As shown in **Table 5**, there was no confidence interval of HTMT for the paths with the value of 1, which indicates the constructs have sufficient discriminate validity (See., Henseler, 2010). Finally, we can conclude that Fornell-Larcker criterion, cross-loading criterion and HTMT revealed that the constructs exhibit sufficient discriminant validity.

Table 4. Discriminant validity (cross-loading criterion)

	AT	BI	PEU	PU	XIT
AT1	**0.9002**	0.5629	0.6434	0.6390	0.4030
AT2	**0.9029**	0.5771	0.6083	0.5408	0.4179
AT3	**0.9176**	0.6430	0.6193	0.5499	0.3764
AT4	**0.9337**	0.5909	0.6170	0.6127	0.4451
BI1	0.6259	**0.8688**	0.4363	0.4446	0.4082
BI2	0.5751	**0.8772**	0.4593	0.4070	0.4187
BI3	0.4766	**0.8140**	0.4172	0.3035	0.2843
BI4	0.5187	**0.8443**	0.4509	0.3709	0.3283
PEU1	0.5414	0.4905	**0.8905**	0.4913	0.3671
PEU2	0.6053	0.4353	**0.9426**	0.4761	0.3431
PEU3	0.5917	0.4641	**0.9188**	0.4650	0.3263
PEU4	0.7119	0.4826	**0.8742**	0.4941	0.4050
PU1	0.5619	0.4150	0.5003	**0.9344**	0.4975
PU2	0.6130	0.4455	0.5339	**0.9411**	0.4744
PU3	0.5953	0.4098	0.4688	**0.9412**	0.4930
PU4	0.6173	0.4164	0.4804	**0.9090**	0.5181
XIT1	0.3716	0.3888	0.3763	0.4219	**0.8835**
XIT2	0.4250	0.3752	0.3637	0.5016	**0.9120**
XIT3	0.4469	0.3965	0.3840	0.4956	**0.9134**
XIT4	0.3589	0.3972	0.3253	0.4962	**0.8876**
XIT5	0.3992	0.3503	0.3342	0.4572	**0.8645**

Table 5. Discriminant validity (HTMT)

	AT	BI	PEU	PU	XIT
AT	-				
BI	0.713	-			
PEU	0.726	0.573	-		
PU	0.689	0.492	0.566	-	
XIT	.480	0.467	0.426	0.564	-

Table 6. Lateral collinearity assessment and hypothesis testing

Hypothesis	Relationship	VIF	Std Error	Std Beta	t-value	P Value	R^2	F^2
H1	XIT → PEU	1.000	0.069	0.400	5.765	0.000	0.160	0.190
H2	XIT → PU	1.190	0.064	0.380	5.971	0.000	0.405	0.204
H4	PEU → PU	1.190	0.071	0.381	5.369	0.000		0.205
H5	PEU → AT	1.396	0.076	0.472	6.217	0.000	0.571	0.372
H8	PU → AT	1.396	0.066	0.390	5.771	0.000		0.254
H3	XIT → BI	1.446	0.073	0.164	2.267	0.024	0.453	0.034
H6	PEU → BI	1.932	0.106	0.117	1.096	0.273		0.013
H7	PU → BI	1.979	0.070	-0.026	0.368	0.713		0.001
H9	AT → BI	2.353	0.087	0.513	5.880	0.000		0.204

Hypothesis Testing

Table 6 presents the results of the assessments of the structural model. First, we addressed the lateral collinearity issue. To assess this, we used the Variance Inflation Factor (VIF). VIF values need to be above 0.2 and below 5.0 (Hair et al., 2017). **Table 7** shows that all the inner VIF values for the independent variable are above 0.2 and below 5.0. Therefore, we conclude that in this study lateral multicollinearity is satisfactory.

Second, t-values for all paths were measured using the bootstrapping function of SMART PLS 3 to examine the significance level. Furthermore, we used Cohen's f^2 to evaluate the effect size of AT and XIT on BI (Cohen, 2013). Overall, **Table 6** shows that seven out of nine relationships are identified as having t-value > 1.645. Therefore, they are significant at a 0.05 level of significance.

Table 7. Summary of hypotheses testing

Hypothesis	Effects	Direction	Path Coefficient	Conclusion
H1	XIT → PEU	Positive	.400	Supported
H2	XIT → PU	Positive	.380	Supported
H3	XIT → BI	Positive	.164	Supported
H4	PEU → PU	Positive	.381	Supported
H5	PEU → AT	Positive	.472	Supported
H6	PEU →BI	Positive	.117	Not supported
H7	PU → BI	Negative	-.026	Not Supported
H8	PU → AT	Positive	.390	Supported
H9	AT → BI	Positive	.513	Supported

Experience in using E-learning (XIT) (β= 0.400, t-value = 5.765, p < 0.001) positively and significantly affects PEU with medium effect size (0.190). Hence, hypothesis 1 is supported. Furthermore, PEU (β= 0.381, t-value = 5.369, p < 0.001) and XIT (β= 0.380, t-value = 5.971, p < 0.001) positively affects PU. Therefore, hypothesis 2 and hypothesis 4 are accepted. In terms of effect size, according to Cohen (2013), f^2 for PEU (0.205) and XIT (0.204) are regarded as medium effect size.

In terms of attitude toward using E-learning (AT), PEU (β= 0.472, t-value = 6.217, p < 0.001) and PU (β= 0.390, t-value = 5.771, p < 0.001) positively affect AT. Therefore, hypothesis 5 and hypothesis 8 are supported. Regarding the effect size of PEU and PU on AT, f^2 for PEU (0.372) and PU (0.254) are considered medium effect size.

Regarding behavioral intention to use E-learning (BI), two out of four relationships were found to have t values > 1.645. Predictors of AT (β= 0.513, t-value = 5.880, p < 0.001) and XIT (β= 0.164, t-value = 2.267, p < 0.05) positively relate to BI. Hence, hypothesis 3 and hypothesis 9 are supported. However, predictors of PEU (β= 0.117, t-value = 1.096, p > 0.05) and PU (β= -0.026, t-value = 0.368, p > 0) do not significantly and positively relate to BI. Therefore, hypothesis 6 and hypothesis 7 are rejected. According to Cohen (2013), f^2 for AT (0.204) is considered as a moderate effect, while f^2 for XIT(0.034) is considered as small effect size. Summary of the results of hypotheses testing is presented in **Table 7**.

DISCUSSION

The main aim of this study is to examine factors that affect secondary school mathematics teachers' behavioral intention (BI) to use E-learning in their teaching. This study is distinct from other studies because it was conducted in the context of COVID-19 pandemic and it investigated teachers who experience using E-learning for their professional development. Hence, it is necessary to examine teachers' behavioral intention to advance our understanding of the factors that play a significant role in teachers' use of E-learning in their teaching, particularly for teachers who have experience in using E-learning for their professional development. To achieve this aim, TAM model (Davis, 1986) was adopted with an addition of an external factor of teacher experience in using E-learning during in-service professional development. The hypotheses related to the directional link between TAM scales and the external factor were examined. Results of this study show three crucial points of discussion.

First, the study suggests that teachers' E-learning experience (XIT) has a significant direct effect on their perceived ease of use (PEU) and perceived usefulness (PU) of E-learning. This finding is consistent with existing studies (Lau & Woods, 2008; Martin, 2012; Pituch & Lee, 2006; Rezaei et al., 2008; Williams & Williams, 2010), confirming the significant effect of experience on users' PEU. Previous studies revealed that users' experience had a significant effect on their PU of E-learning (Lee et al., 2013; Martin, 2012; Rezaei et al., 2008). Teachers, throughout their careers, had many chances to participate in online professional development to develop their content knowledge and pedagogical knowledge. For instance, in the Indonesian context, for the last two years the government provided in-service teachers online certification programs. This study shows that such training, to some extent, has affected teachers' PU and PEU of e-learning for their teaching. Therefore, this study indicated that teacher online professional development has positive impact on not only teacher knowledge development but also on their acceptance of e-learning for their instructional purpose. The effectiveness of online teacher professional development has received much intention from research around the world. Therefore, it enriches the literature in terms of advancing our understanding of teachers' perceived ease of use and perceived usefulness of e-learning for their instruction.

Second, regarding attitude of use (AT), the results show that PEU (β= 0.472, t-value = 6.217, $p < 0.001$) and PU (β= 0.390, t-value = 5.771, $p < 0.001$) appear to be strong predictors of AT. Previous studies have shown the importance of PU and PEU for attitude toward using E-learning (Hamid et al., 2016; Hess et al., 2014; Mou et al., 2017). Therefore, this finding is consistent with our hypothesis that teachers' PEU and PU of E-learning positively and significantly affect their attitude toward using E-learning.

Third, regarding teachers' behavioral intention to use E-learning (BI), the results suggest that AT (β= 0.513, t-value = 5.880, $p < 0.001$) is the strongest predictor of BI, followed by XIT (β= 0.164, t-value = 2.267, $p < 0.05$). Previous studies also have proved the importance of attitude (AT) as an intrinsic motivator for behavioral intention (Hussein, 2017; Letchumanan & Tarmizi, 2011; Sharma & Chandel, 2013; Taat & Francis, 2019). In addition to that, the findings of this study that experience impacts users' intention to use E-learning are in line with findings in previous studies (De Smet et al., 2012; Premchaiswadi et al., 2012; Williams & Williams, 2010). Another result reveals that PEU (β= 0.117, t-value = 1.096, $p > 0.05$) and PU (β= -0.026, t-value = 0.368, $p > 0$) are not significantly and positively related to BI. Several past studies showed similar findings that PU (Lew et al., 2019; Park, 2009; Yuen & Ma, 2008) and PEU (Lew et al., 2019) were non-significant for the prediction of behavioral intention to use E-learning. However, the other previous studies found the opposite, that perceived ease of use (PEU) and perceived usefulness (PU) directly influence intention to use E-learning (Al-Gahtani, 2016; Elkaseh, Wong, & Fung, 2016; Hsia, Chang, & Tseng, 2014; Lee, Hsiao, & Purnomo, 2014; Tarhini et al., 2016; Tarhini, Hone, & Liu, 2014).

Regarding the context of this study, there are two possible reasons why PU and PEU are not crucial in teachers' behavioral intention to use E-learning in teaching. First, the participants were teachers who had long experience in using E-learning for their online professional development. Lin (2011) found a similar finding that suggests PEU has a more critical impact on intention of less experienced users than more experienced users. These results are consistent with the finding of another study (Castañeda, Muñoz-Leiva, & Luque, 2007), in the context of intention to use the website, showing that PEU is a more important factor for less experienced users than for more experienced users. Therefore, this indicates that, for experienced teachers, perceived ease of use does not play significant role in their adoption of e-learning for teaching purpose. For experienced teachers, other factors play such as attitude play much more significant role then perceived ease of use does. The reason for this lies in the fact that different individual view e-learning from perspective. For example, in the context of the use of a website, Castañeda et al. (2007) revealed that the experience users are more interested in the outcome of search while new users evaluate the website the novelty of the site. In other words, Castañeda et al. (2007) argued that experienced users are influenced by extrinsic motivation while new users are influenced by intrinsic motivations such as perceived ease of use. Second, according to Davis (1993), perceived usefulness is the expected overall positive impact of system use on job outcome while PEU is the extent to which a user thinks that using a system will be free of effort. In the context of this study, the data collection took place during the COVID-19 pandemic when school closure left students and teachers dependent on E-learning. In such circumstances, when the teachers do not have other options for remote teaching, perceived usefulness and perceived ease of use of E-learning might become less important factors in teachers' decisions to use or not to use E-learning.

For that reason, this study leaves room for debate on this issue and future work is necessary to explore it.

The findings of this study indicate that having experience in using E-learning for teacher professional development does not guarantee that teachers will use E-learning in their teaching. For this type of teacher, attitude is the crucial factor that determines their use of E-learning technology in their instruction. However, having teacher training experience positively affects their perceived usefulness and perceived ease of use of E-learning. Therefore, if schools and policymakers would like to enhance the integration of E-learning in secondary schools, particularly during the pandemic, along with providing training for teachers, much more effort is needed to ensure teachers have strong intentions to adopt technology and more importantly to ensure that teachers possess a strong positive attitude toward the E-leaning system.

CONCLUSION

This study revealed factors that determine teachers’ behavioral intention to use E-learning in their mathematics teaching, particularly teachers who have experience in using E-learning for their professional development. The results showed that two out of four exogenous constructs have a positive effect on teachers’ behavioral intention to use E-learning, namely attitude toward using, and experience in using E-learning. Teachers’ attitudes toward using E-learning plays the most significant role in their behavioral intention. In addition, E-learning experience positively and significantly affects teachers’ attitude toward E-learning. This study suggested that, for experienced teachers, perceived ease of use and perceived usefulness did not have a significant positive impact on teacher behavioral intention.

There are several limitations of this study that need to be addressed in future studies. First, the participants of this study were teachers who participated in an online teacher professional development program in one HEI assigned by the Indonesian government. This condition may influence the generalizability of the finding of this study. Therefore, further research is needed to validate this model in other HEIs. Second, the present study revealed that perceived usefulness (PU) and perceived ease of use (PEU) did not have a significant positive effect on teachers’ behavioral intention to use E-learning. Thus, future research should aim to explore this issue in the context of teachers who experienced using E-learning for their professional development. Finally, this study has one external factor, namely E-learning experience. However, additional external factors of behavioral intention may also exist. As a result, future work should consider other external variables, such as school facilities and support for the integration of E-learning.

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