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Research Article

Vietnamese Teachers' Acceptance to Use E-Assessment Tools in Teaching: An Empirical Study Using PLS-SEM

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ABSTRACT

The purpose of this study is to examine factors that influence teachers' intentions to use technology in assessments using the technology acceptance model (TAM) as a framework. An online survey was utilized to collect data, and 360 teachers participated in the survey. This study used partial least squares-structural equation modelling (PLS-SEM) to test the hypotheses to verify the effects of variables on teachers' intention of e-assessment use. The model consists of four constructs: computer self-efficacy (CE), perceived ease of use (PEOU), perceived usefulness (PU), and frequent use of e-assessment tools (FoUAT). The findings revealed a significant influence path from CE to PEOU, FoUAT, and behavior intention. In addition, PEOU is a critical factor that positively impacts both PU and teachers' behavior intentions. In contrast to our expectation, frequency of use was statistically insignificant and had no impact on teachers' intention to use (IU) e-assessment tools. The total of these four variables corresponded to 71.4% of the variance of user intention. These results confirm that TAM is an effective model to explain teachers' technology acceptance to use e-assessment tools for their teaching.

Keywords: computer self-efficacy, e-assessment tools, PLS-SEM, technology acceptance model

INTRODUCTION

In the modern era, every aspect of our life is strongly affected by technology, particularly its integration into users' private and professional life. Users' acceptance or rejection of technological applications in different fields, including education, has garnered much attention from researchers (Granic & Marangunic, 2019; Marangunic & Granic, 2015). Although there have been many research models in this field, the technology acceptance model (TAM), introduced by Davis (1989), became one of the most critical models related to the factors affecting the adoption by users in using technology. In addition, the importance of applying technology in teaching and learning activities has been emphasized (Davis, 2011; Davis et al., 2011; Scherer et al., 2019). Among these activities, assessment is one of the key factors in educational practice.

E-assessment, with alternative names of electronic assessment, computer-based assessment, digital assessment, or online assessment (Kundu & Bej, 2020), consists of the whole process from the design of tasks to archiving results. It can be used for formative or summative purposes (Appiah & Van Toner, 2018). Schools can decide to use already-built assessment tools merged into a learning management system (LMS) or use separated assessment tools (Conole & Warburton, 2005). While Moodle can be used in both summative and formative assessment, other applications such as Google Forms, Quizizz, Mentimeter, Powtoon, or Kahoot are preferred in formative assessment. Using those applications may create games, quizzes, discussions, surveys, and assessments for their students. To meet their specific needs, the education institutions and teachers can customize these open resource tools (Appiah & Van Toner, 2018).

Being aligned with global trends, in 2018, the Ministry of Education in Vietnam released a school teacher standard decree in which computer technology competence was one of the five compulsory criteria. Teachers were asked to integrate technology to improve teaching; however, how they use assessments remains unchanged, with the paper-test format being their primary assessment method until the COVID-19 pandemic commenced. During the increased concerns over COVID-19, all schools in Vietnam were required to switch to online learning. Thus, teachers must find e-assessment tools to replace their traditional evaluation methods. This abrupt change led to several consequences—for example, the un-preparedness of both teachers and schools and students' passiveness. Even though teachers may have some prior experience employing several technology tools in teaching, the e-assessment requires more effort and time to become proficient. As a result, the resistance to exploring technology and e-assessment tools remains high.

Whether users accept or feel reluctant to use technology in teaching and learning, especially e-assessment tools, attracts vast attention. The TAM developed by Davis (1989) has been one of the most common theories in e-learning acceptance literature (Abdullah & Ward, 2016; Weerasinghe & Hindagolla, 2017). This model with two primary constructs: perceived ease of use (PEOU), and perceived usefulness (PU) originated from the theory of reasoned action. These two elements affect the attitudes towards the system and are influenced by external variables. Although many different acceptance studies in education have been exploring TAM (Ibrahim et al., 2017; Sanchez-Prieto et al., 2016), the studies related to the adoption of users in e-assessment using TAM and related studies in Vietnam are rare.

THEORY RELATED LITERATURE

TAM was first introduced by Davis in 1989 (Davis, 1989). TAM was originally made up of key variables of internal motivation (PEOU, PU, and attitude toward using) as well as outcome constructs (behavioral intentions, actual system use) (Scherer et al., 2019). In the past years, researchers have discovered new variables such as online features, user characteristics (Witz & Göttel, 2016), subjective norm (Scherer et al., 2019), anxiety (Rizun & Strzelecki, 2020), computer self-efficacy (CE) (Mukminin et al., 2020), etc. and adjusted the relationship between previously identified TAM components.

Among external variables in TAM, CE is one of the factors directly impacting PEOU and PU (Ngabiyanto et al., 2021). In addition, Al-Emran et al. (2018) argued that the intention to adopt e-learning could be influenced by multiple significant factors, including PEOU, PU, and others. This paper develops an extension model of TAM with CE and frequent use of e-assessment tools (FoUAT), integrated with PEOU and PU as two fundamental factors of the original model. In the following sections, each variable in the suggested model is explained in details.

Computer Self-Efficacy

Self-efficacy is what users believe in carrying out necessary activities to fulfill a particular work task (Venkatesh & Davis, 1996). As a result, boosting the degree of CE among students improves their acceptance (Mouakket & Bettayeb, 2015). CE has been regarded as a critical determinant (Al-Emran et al., 2018). It helps a lot in improving academic results (Cheng & Tsai, 2011). Research results have shown that CE positively impacts PEOU (Yalcin & Kutlu, 2019). However, Chang et al. (2017) pointed out that CE would have no impact on PU of e-learning system. Also, Purnomo and Lee (2013) stated in their studies that CE has no impact on users' system adoption, and it only helps users experience more with the system, which is against the previous studies on technology acceptance (Zainab et al., 2017). Therefore, the following hypotheses are formed:

H1a: CE positively affects intention to use (IU) e-assessment tools

H1b: CE positively affects FoUAT

H1c: CE positively affects PEOU

H1d: CE positively affects the PU

Perceived Ease of Use

Davis (1989), Venkatesh et al. (2003), and Wirtz and Göttel (2016) have confirmed the correlations between PEOU and PU, as well as between PEOU, PU, and IU. According to Eraslan and Kutlu (2019), the most important constructs in TAM are PEOU and PU. In Davis' (1989) first paper introducing TAM in 1989, PEOU was defined as "the degree to which the person believes that using a particular system would be free of effort." Many researchers stated that PEOU positively affects PU and users' IU a particular technology (Eraslan & Kutlu, 2019). However, Chang et al. (2017) pointed out that PEOU does not affect PU of e-learning system. For that, in this paper, we test the following hypothesis:

H2a: PEOU positively affects IU e-assessment tools

H2b: PEOU positively affects FoUAT

H2c: PEOU positively affects PU

Perceived Usefulness

PU is one of the key constructs in TAM and its extended versions. Davis (1989) defined PU as "the degree to which a person believes that using a particular system would enhance his/her job performance." According to AQlsabawy et al. (2016), researchers have regularly employed PU in the field of e-learning systems. In fact, the e-learning research literature, PU is the primary determinant affecting users' intention (Al-Emran et al., 2018; Kanwal & Rehman, 2017), which means customers intend to use a technology when they find it useful for their work or they use it more often. Hence, the following hypothesis is formulated:

H3a: PU positively affects FoUAT

H3b: PU positively affects IU e-assessment tools

Frequent Use of E-Assessment Tools

In addition to PEOU, PU, and CE, FoUAT is also an important factor in the model. FoUAT means the level of frequency that users use e-assessment tools in their teaching activities. FoUAT is selected in the model because according to Abdullah and Ward (2016), experience with the system or tools is one of the most commonly used external factors in e-learning acceptance studies. Therefore, this study will examine the relationship of the key constructs in TAM as well as the new construct of frequent use on teachers' IU, which has never carried out in the e-assessment related studies. Therefore, we hypothesize that FoUAT may be affected by PEOU, PU, and CE.

H4: FoUAT positively affects IU e-assessment tools

As shown in **Figure 1**, our research model uses TAM for a theoretical basis. According to our model, teachers' IU e-assessment tools is directly influenced by their perception of usefulness and ease of use and FoUAT. CE indirectly affects users' intention via its impact on PU, ease of use, and FoUAT.

RESEARCH METHOD

Participants and Procedure

This study explores teachers' willingness from all levels of the education system (pre-school, primary school, junior high school, and senior high school) in Vietnam using e-assessment tools. According to the Ministry of Education and Training (MOET, 2021), the population of K-12 teachers was 993,788 in the 2019-2020 academic year. We selected a sample of 385 teachers from this population. A convenient sampling approach was adopted to verify the hypotheses. An approximate 10-minute-online survey was designed using Google Forms and sent by email, message, and Zalo to teachers teaching online in July 2021 when the academic year ended. Zalo is a popular social media platform in Vietnam like WhatsApp or Facebook. 360 teachers, who use e-assessment tools during their lessons, completed the survey for our analysis and accounted for a 93.51% response rate. This number of participants meets the criteria for conducting the model analysis. It is greater than the 113 samples required to detect a minimum R-square (R^2) of 0.10 at a significance level of 5% for an 80% statistical power (Cohen, 2013). The sample consisted of 84.7% female teachers and 15.3% male teachers. 37.5% of the respondents were senior high school teachers, 34.7% were

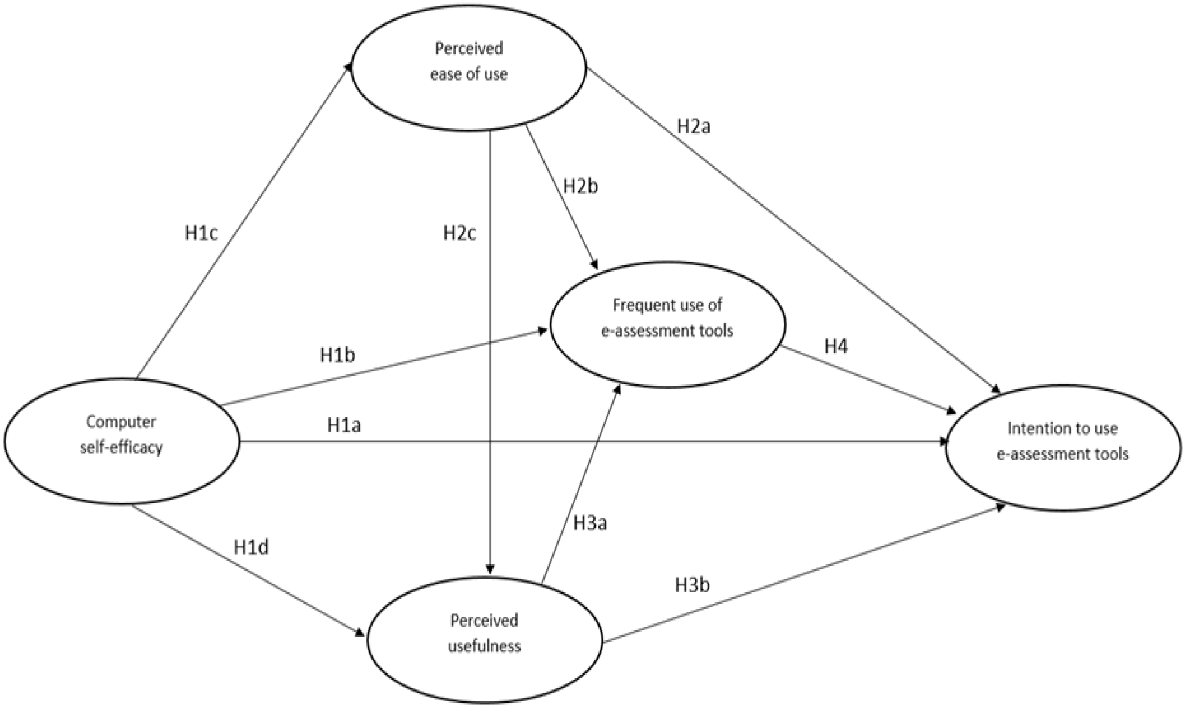

Figure 1. Proposed research model

Table 1. Demographic information

Item	Values	Frequency	Percentage
Gender	Male	55	15.3
	Female	305	84.7
School Level	Pre-school	66	18.3
	Primary school	34	9.4
	Junior high school	125	34.7
	Senior high school	135	37.5
Subjects	Math and science	224	63.5
	Literature and social science	30	8.5
	Foreign language	12	3.4
	Art and others	87	24.7

junior high school teachers, 9.4% were primary school teachers, and 18.3% were pre-school teachers. More demographics of participants are detailed in **Table 1**.

Instrument

As with other studies on technology acceptance, this study references the main research instrument of Davis et al. (1989) and other studies such as Ariff et al. (2012) and Purnomo and Lee (2013). There are three different steps for a survey. The first step is to collect demographic information such as school level, gender, race, and teaching subjects. The second step focuses on data collection of teachers' CE and FoUAT. The third step is to collect data on the TAM factors. These TAM factors include the PEOU, the PU, and the IU. A five-point Likert scale ranging from 5 "strongly agree" to 1 "strongly disagree" is used on all these items that were measured in the last two steps of a survey.

Data Analysis

The data for this study were analyzed using partial least squares-structural equation modelling (PLS-SEM) to test the proposed model developed with smart-PLS 3.3. Because this study is exploratory based-research, its methodology implements a variance-based structural equation modeling approach for multivariate analysis, which allows for the inclusion of more adjustable assumptions while providing an accurate examination of the model's predictive hypotheses (Garson, 2016).

Table 2. Descriptive statistics of the items of the extended TAM and indicator level hypothesis contrast

Item	Mean	SD	Med	Asymp.Sig. gender[a]	Asymp.Sig. school-level[b]	Asymp.Sig. subjects[b]
PU1	4.097	0.839	4	0.254	0.480	0.317
PU2	4.042	0.876	4	0.430	0.365	0.204
PU3	4.219	0.823	4	0.730	**0.039**	0.073
PEOU1	4.364	0.784	4	0.404	0.827	**0.022**
PEOU2	4.336	0.796	4	0.971	0.812	0.782
PEOU3	3.847	0.886	4	0.341	**0.001**	**0.000**
UI1	4.253	0.810	4	**0.036**	0.441	**0.020**
UI2	4.256	0.786	4	0.419	0.485	0.492
UI3	4.003	0.825	4	0.178	**0.004**	**0.025**
CE1	4.081	0.804	4	**0.050**	0.728	0.095
CE2	3.953	0.844	4	**0.026**	0.780	0.096
CE3	3.703	1.002	4	0.228	0.268	0.491
FoUAT	3.103	0.780	3	0.563	**0.010**	0.849

Note. [a]Asymptotic significance results of Mann-Whitney's U; [b]Asymptotic significance results of Kruskal Wallis test

According to Hair Jr et al. (2017), this method has two significant advantages compared to covariance-based structural equation model analysis. First, this technique allows for the inclusion of variables modeled as formative composites and the evaluation of the weight of each of its indicators. Second, this approach is geared toward the prediction of a target variable as well as the assessment of the predictive power of its antecedents.

RESULTS

Descriptive Statistics

The study's data sample shows the responses collected from 360 teachers in different level schools. We aim to assess teachers' attitudes towards the use of e-assessment tools in their future teaching practice. As shown in **Table 2**, the results indicate that teachers are inclined to use e-assessment tools in their future teaching practice, with scores above 3 out of a maximum of 5 in most items; the median scores in all the indicators are between 3 and 4. Two of three items related to constructs of CE and one of three terms of PEOU construct have obtained value under 4. The frequency of using e-assessment tools has one item with a mean under 4 as well.

We used the normality tests of Kolmogorov-Smirnov and Shapiro-Wilk to assess the sample's normality to choose the best analysis technique. The normality hypothesis was rejected because of these analyses (sig<0.05). Following that, we calculated the kurtosis and skewness coefficients to determine how much the factors concentrated around the central zone of the distribution. The obtained results show that no extreme values prevent us from performing the intended PLS analysis. Finally, to determine whether there are differences at an indicator level based on teacher gender, school level, and teaching subjects, we used non-parametric statistics to see significant differences in the mean scores obtained by teachers grouped according to these variables.

Table 2 also includes the results of the Kruskal-Wallis test's asymptotic significance for the variable school level and teaching subjects and Mann-U Whitney's for the variable gender. We discovered statistically significant differences in 3 of the 13 instrument items for the variable gender (sig< 0.05). Male teachers receive slightly higher scores than female teachers in all of them. There are statistically significant differences in 4 of the 13 instrument items for the variable school level (sig<0.05) and in 4 of the 13 instrument items for the variable teaching subjects (sig<0.05).

In addition, we investigated the online assessment tools teachers often use. The most commonly used evaluation tool was Google Forms (60%), followed by Quizizz, Kahoot, and other tools such as Mentimeter, SHub Classroom, Google Classroom, and some school-designed online assessment apps (**Figure 2**).

Measurement Model Assessment

The assessment of the measurement model is based on reliability and validity. The factor loading should be measured to determine the item's reliability. Hair Jr et al. (2021) consider an "equal to or greater than 0.7"

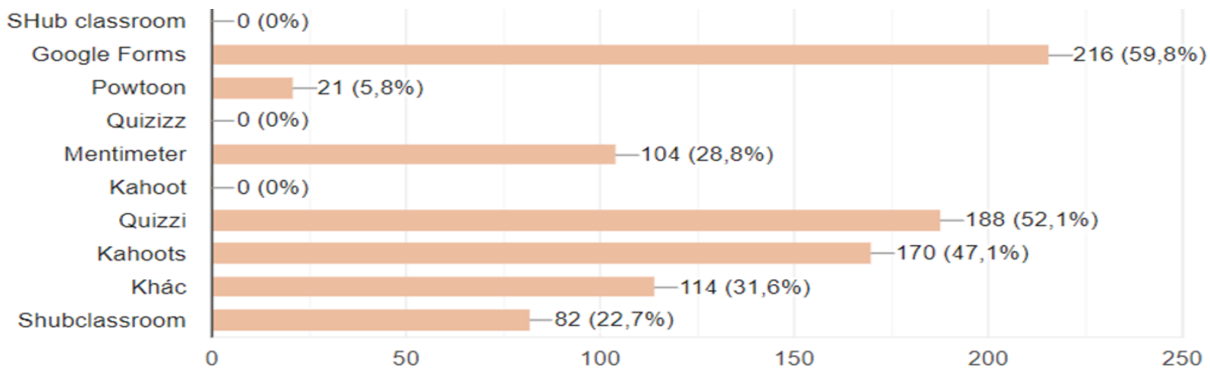

Figure 2. Online assessment tools that teachers often use

Table 3. Item reliability and convergent validity analysis of the reflective variables

Constructs	Items	Loadings	Cronbach's alpha	CR	AVE
PU	PU1	0.872			
	PU2	0.870	0.853	0.892	0.735
	PU3	0.829			
PEOU	PEOU1	0.864			
	PEOU2	0.856	0.787	0.876	0.701
	PEOU3	0.790			
IU	UI1	0.906			
	UI2	0.878	0.853	0.910	0.772
	UI3	0.850			
CE	CE1	0.900			
	CE2	0.909	0.853	0.896	0.743
	CE3	0.769			

Table 4. Fornell-Larcker criterion results

	CE	UI	PEOU	PU	FoUAT
CE	0.862				
UI	0.644	0.878			
PEOU	0.647	0.762	0.838		
PU	0.521	0.785	0.772	0.857	
FoUAT	0.179	0.029	-0.011	0.018	1.000

threshold for each item's loading reliable. In addition, Cronbach's alpha and composite reliability scores should also be more than or equal to 0.7.

Table 3 shows that all products are dependable and satisfactory. The average variance extracted (AVE) is defined as the grand mean value of the squared loadings of the construct-related items and the standard measure for determining convergent validity. An AVE score of 0.5 or above indicates that the concept explains more than half of the variation of its items (Hair Jr et al., 2017). **Table 3** shows that Cronbach's alpha and composite reliability (CR) values are greater than 0.7, and AVE values are greater than 0.5. Therefore, the convergent validity of the constructs is established.

The discriminant validity was assessed using Fornell and Larcker's (1981) criterion, a well-known method to measure how constructs are distinct from each other in a model. Fornell and Larcker (1981) criterion stated that the square root of AVE comes in a diagonal place, and it should be higher than the other constructs' correlation values. The results in **Table 4** show that all diagonal values are higher than the corresponding correlation values, which reflects the model is discriminant valid.

Structural Model Assessment

After confirming the measurement model's reliability and validity, structural model analysis was assessed to determine the percentage of variation predicted by relationships among the constructs. The structural model explains the relationship between the latent constructs (Hair Jr et al., 2017). Hypothesis testing and coefficient of determination R^2 are suggested to be tested to measure the structural model. **Table 5** and

Table 5. R-square

	R-square	T-statistics	p-Values
PEOU	0.418	5.925	0.000
PU	0.572	9.195	0.000
FoUAT	0.051	2.005	0.045
UI	0.714	15.525	0.000

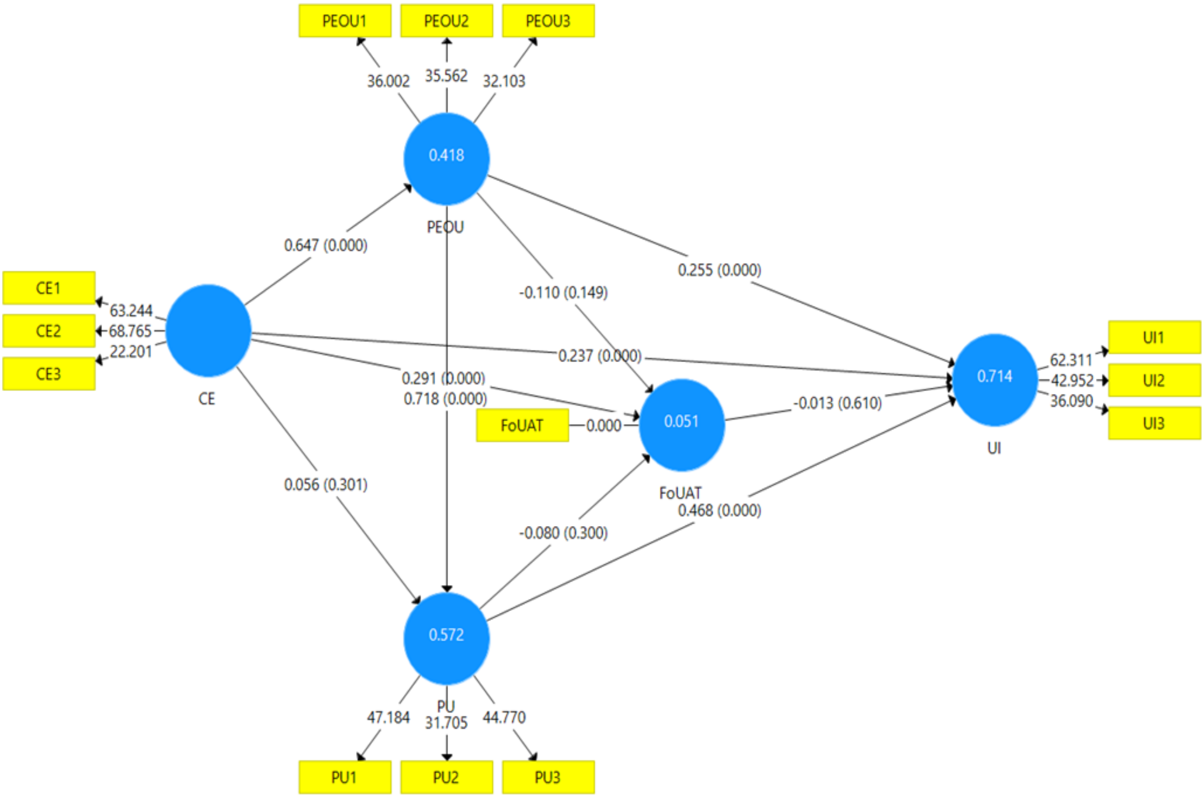

Figure 3. Path analysis results

Figure 3 summarize the findings, which show that four hypotheses are supported. The empirical results supported six hypotheses, including H1a, H1b, H1d, H2a, H2c, and H3b. However, hypotheses H1c, H2b, H3b, and H4 were rejected based on the data analysis.

By measuring the amount of variation in the model's dependent variables, we can assess the model's explanatory power. The R^2 and path coefficients are essential for evaluating the structural model (Hair Jr et al., 2017). Chin (1998) explained the R^2 values greater than the cutoffs 0.67, 0.33, and 0.19 to be substantial, moderate, and weak, respectively. **Table 5** shows that the model has an R^2 value of 41.8% for PEOU, 57.2% for PU, 5.1% for FoUAT, and 71.4% for UI, T statistic values greater than 1.96 and p-values less than 0.05 indicated that the model was significant.

The path coefficients of the constructs were found to be the primary determinants of the intention of e-assessment tools. **Table 6** lists down the path coefficients, observed t-value, and significance level for all hypothesized paths. Path analysis is used to determine whether the hypotheses are accepted or rejected. The results revealed that the relationships between the original TAM constructs (Davis, 1989) are demonstrated. PEOU significant influenced PU (β=0.781, $p<0.001$) and UI (β=0.490, $p<0.001$) supporting hypothesis H2c and H2a respectively. Additionally, PU has a positive effect on UI (β=0.468, $p<0.001$) supporting hypothesis H3b.

The findings showed that PEOU did not significantly influence FoUAT and PU ($p>0.05$), not supporting hypothesis H2b and H3a, respectively. In addition, the relationship between FoUAT and UI is not significant ($p>0.05$), so hypothesis H4 is rejected. CE was found to have significantly influence on UI (β=0.237, $p<0.001$), PEOU (β=0.647, $p<0.001$), and FoUAT (β=0.294, $p<0.001$) supporting hypothesis H1a, H1b, H1d respectively. However, CE has no significant relationship with PU ($p>0.05$), so hypothesis H1c was rejected.

Table 6. Hypotheses test results

Hypothesis	Path	Coefficient	p-value	Results
H1a	CE->UI	0.237	0.000	**Accepted**
H1b	CE->PEOU	0.647	0.000	**Accepted**
H1c	CE->PU	0.056	0.301	Rejected
H1d	CE->FoUAT	0.294	0.000	**Accepted**
H2a	PEOU->UI	0.490	0.000	**Accepted**
H2b	PEOU->FoUAT	0.027	0.297	Rejected
H2c	PEOU->PU	0.781	0.000	**Accepted**
H3a	PU->FoUAT	-0.080	0.300	Rejected
H3b	PU->UI	0.468	0.000	**Accepted**
H4	FoUAT->UI	-0.013	0.610	Rejected

DISCUSSION

In this present study, we explored the driving forces of technology acceptance for e-assessment tools among school teachers in Vietnam, where traditional teaching and learning with paper test assessments are dominant. Consequently, teachers and students have little chance to access and use technology. Finding the factors affecting technology acceptance and applying e-assessment tools is crucial to preparing teachers and students for the future of integrating technology in teaching and learning.

First, the results of this study reveal a significant influence path from CE to PEOU, FoUAT, and UI. This finding is consistent with existing studies (Hong et al., 2021; Mailizar et al., 2021), confirming that CE and teachers' experience with technology affect their PEOU and UI. Our analysis suggests that the higher the level of CE, the more frequently teachers use the e-assessment tools. Likewise, the level of CE influences whether teachers perceive e-assessment tools as easy or difficult, which affects their decision to use e-tools for their assessments. In COVID-19, Vietnamese teachers have to quickly find and use e-assessment in their teaching. As a result, they are likely to choose the tools that take less time and effort to master. Hence, as data shows, most teachers of all levels choose simple tools such as Google Forms, Quizizz, and Kahoot. The direct and indirect significant impacts of CE on teachers' IU e-assessment tools highlight the need to enhance teachers' computer competence, increasing their technology acceptance in the future.

Second, the study result contradicts findings of Lew et al. (2019) and Stockless (2018) but aligns with studies such as Hong et al. (2020), Huang et al. (2020), and Venkates et al. (2003) confirms that PEOU has a positive and significant impact on PU and users' intention. In other words, PEOU is a critical driver for teachers' decision for e-assessment tools acceptance either directly or indirectly via PU. Rafique et al. (2020) have pointed out that the swift switch to online learning requires proper preparation, whilst most teachers do not have adequate experience with online education. The study results suggest that there exist a comfortable threshold affecting teachers' IU technology and experience further with more advanced or complicated tools because they do not have extensive experience with e-assessment tools and have difficulty in actual technology usage. Therefore, it is essential to encourage teachers to adopt simple and basic e-assessment tools early to reinforce inceptive technology acceptance before employing complex ones. Otherwise, they may refuse to utilize the e-assessment tools in their teaching if it requires too much effort.

Third, without considering CE factors, the result of direct variables influencing users' intention demonstrates that PU has a higher effect than PEOU. This result contradicts the findings obtained by Hong et al. (2021), and Yuen and Ma (2008). However, it is consistent with the findings of Baydas and Goktas (2017) and Teo et al. (2012) that teachers would rather see the usefulness before forming an IU than simply accepting the technology because it is easy to operate. A possible explanation for this remarkable finding could be that PEOU is crucial for beginners; once teachers comprehend the technology and become confident with their technology efficacy, their mindset options may change. Therefore, school managers and administrators should consider providing training to foster teachers' computer efficacy to overcome barriers to effectively exploit the more valuable tools among the abundant resources for their teaching.

Fourth, judging from statistical significance, it is noteworthy that CE directly impacts PEOU but imposes no significant effect on PU. The result contradicts the finding of Ngabiyanto et al. (2021) and Teo et al. (2014) that CE directly affects both constructs. Also, according to our results, the impact of PEOU and PU on the FoUAT are not statistically significant. In other words, teachers' perception of technology usefulness and ease of use does not affect the degree to which teachers use e-assessment. Likewise, although FoUAT receives a significant direct effect from CE, it imposes no effect on users' intention. In the extraordinary circumstance of COVID-19, teachers had no option but to use e-assessment tools for their teaching. Hence, teachers were forced to adopt the technology; their behavior was influenced by the degree they perceived the usefulness and ease of use of the tools than the frequency they had to use the tools.

CONCLUSION

The results confirm that TAM is an effective model to explain teachers' technology acceptance to use e-assessment tools for their teaching. Overall, our model exhibits a good fit for data collected with four variables and explains 71.4% of teachers' IU e-assessment tools. The findings reveal that CE, PEOU, and PU impact teachers' IU e-assessment tools. CE and PEOU are critical factors to consider when teachers start to get familiar with and decide to use technology tools in their assessments.

Judged by the influence of four factors, the findings reveal that CE, PEOU, and PU impact teachers' IU e-assessment tools. As education advances, more and more students get familiar with ICT and become fluent, they would prefer integrating technology in their learning. Consequently, the pressure on teachers to efficiently utilize technology in teaching and assessment elevates. Therefore, it is necessary to provide technical support and training for teachers to improve their technology skills to use technology effectively and with ease leading to their willingness to use more e-assessment tools and technology. In addition, consistency in developing criteria for e-assessment and the amount of e-assessment in the school curriculum is crucial to increase the adoption of e-assessment tools in teaching and learning. In addition, further studies could investigate the extent of CE on users' intention and analyze the effect of other aspects such as school support and teaching requirements on teachers' e-assessment tools. Teachers should be more motivated, encouraged, and willing to apply e-assessment tools if they receive support and clear guidance from schools.

There are several limitations of this current research. First, due to practical constraints, this paper cannot comprehensively investigate other variables such as culture, cognition, subjective norms, and emotion affecting teachers' IU e-assessment tools. Second, this study employed an e-questionnaire; therefore, e-assessment tools in teachers' self-reports might differ from the actual practice. Future studies could use observation and interviews to obtain more qualitative data and verify the e-assessment practice of teachers for a better understanding of teachers' adoption and acceptance of e-assessment tools

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