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PREDICTING EFL LEARNERS' SELF-REGULATED LEARNING THROUGH TECHNOLOGY ACCEPTANCE MODEL

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Abstract: The purpose of this study is to assess the perceived usefulness of technology (PUT), internet self-efficacy (ISE), perceived ease of use of technology (PEUT), and self-regulated learning (SRL) of EFL student teachers who participated in technology-mediated English learning environment. After obtaining and validating the questionnaire adapted from several

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relevant sources, an online survey was conducted with 363 third- and fourth-year student teachers of the English education department in Indonesian universities who met the required criteria. SEM was performed to test three hypotheses about the causal relationship between variables. Due to the hypotheses tested, it is revealed that ISE and PEUT have a partially positive and significant effect on SRL, while PUT has a positive but insignificant effect on SRL. Additionally, it is determined that the exogenous variables (PEUT) is the most influential variable on the endogenous variables (SRL). These findings are expected to add to a body of knowledge, particularly in the development of learning autonomy in teacher education, and that ISE and PEUT, in particular, should be considered as important predictors of SRL in technological English learning settings.

Keywords: *internet self-efficacy, perceived ease of use of technology, perceived usefulness of technology, self-regulated learning, technology- mediated English language learning*

INTRODUCTION

The increased accessibility of technology stimulates scholars' interest in researching technology adoption in the context of education (Mei, 2019; Liaw & Huang, 2013; Lai et al., 2016; Sulistyo et al., 2023; Entusiastik & Yuniar, 2022). The study, for instance, acknowledged that online training platforms give language learners the chance to employ technology for language learning and encourage increased motivation as well as better language knowledge and skills (Lai et al., 2016). According to Liaw and Huang (2013), the online environment makes it easier for students to demonstrate the usefulness of technology which can motivate them to practice their self-regulation skills in their learning experiences. The use of information and communication technology (ICT) in the classroom, according to Scherer et al. (2015), considerably increased students' confidence in their ability to utilize the internet.

When technology is included into learning activities, perceived usefulness of technology is linked to learning independence (e.g., Lai & Gu, 2011; Zheng et al., 2016; Lai, 2013; Tsai, 2009; Liaw & Huang, 2013) and enables learners to develop their written and oral skills, grammar, vocabulary building and pronunciation improvement as well (Hani, 2014). Specifically, studies claimed that learning application tools have shown its great contribution to learner's reading upgrading (Yaghoobi & Razmjoo, 2016) and effectively develop students' writing output which is more accurate (Yeh et al., 2014). Due to its usefulness, technology can improve learning situations where students are encouraged to plan and manage their learning, study information, and evaluate their learning process (Artino & Stephens, 2009). According to Sharma et al. (2007), students' self-regulation can be improved in an e-learning environment, particularly in terms of self-efficacy beliefs and goal setting. Online learners can demonstrate higher levels of self-control (e.g., Serwatka, 2003; Broadbent & Poon, 2015; Golladay et al., 2000). Thus, it is clear that the technology learning environment encourages learners to use their metacognitive and cognitive strategies (Narcis et al., 2007) and motivation in their learning to achieve goals successfully and confidently.

According to several studies, students with stronger internet self-efficacy (ISE) demonstrate self-regulation skills, such as information seeking (Tsai & Tsai, 2003; Rains, 2008) and problem solving (Holden & Rada, 2011; Askar & Umay, 2001). When mentors fail to give students the information that they need to solve a problem, they must seek help from another source or from someone. Conditions like this make online technology a means by which their self-control abilities are formed or built (Liu, 2017).

Perceived ease of use of technology can be identified when technology facilitates users to use technology to perform their particular behaviour (i.e. learning behaviour) without little or no effort. For example, using mobile device applications (Apps), students can easily access virtual learning anywhere and engage in access and communication of learning-related information (Dennen & Hao, 2014). Ease of use of a mobile learning educational environment allows students to learn, collaborate, and share ideas with the help of the internet and technological developments (Hamid & Chavoshi, 2018).

Considering previous research findings, less of attention of studies focusing on investigating the causal relationship of perceived usefulness of technology (PU), internet self-efficacy (ISE), perceived ease of use of technology (PEUT), and self-regulated learning (SRL) simultaneously in the context of technology-mediated English language learning using structural equation modeling (SEM). Several studies discussed separately and did not give a comprehensive overview of how the four constructs correlated simultaneously in the context of technology-mediated English learning. For examples, the following studies just focused on examining their relationships among their own dimensions: PU (e.g., Scherer et al., 2015), ISE (e.g., Chuang, et al., 2015), SRL (Zeng et al., 2018), as well as TPACK (e.g., Schmid et al., 2020; Baser, 2015). As a result, the present research focuses on the investigation of the causal relationships among variables, PU, ISE, SRL, and PK and learn the pattern of the relationships in order to find a fit model.

The present study focuses on assessing the causal relationship among the variables, perceived usefulness of technology, internet self-efficacy, perceived ease of use of technology, and self-regulated learning and learns the pattern of the relationships in order to identify a fit model. It is hoped that the results of this research can contribute to the development of learning autonomy, especially in the context of learning of English in teacher education.

METHOD

Research Design

This study employs structural equation model (SEM) to examine theories about causal relationship among the constructs (Meredith et al., 2003) and combine two multivariate techniques, factor analysis and regression, allowing this study to simultaneously examine relationships among the observed variables with their latent variables as well as between latent variables (Hair et al., 2014). It is to examine the causal relationship between the variables of perceived usefulness of technology (PUT), internet self-efficacy (ISE), and ease of use of technology (PEUT) on student teachers' self-regulated learning (SRL) (SRL) and to find a fit model (see Figure 1)

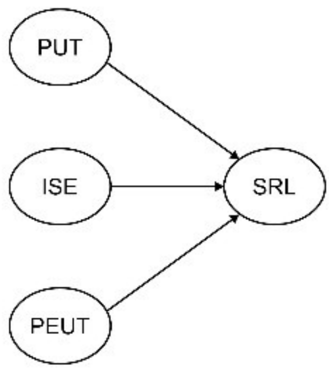

Figure 1. Research design of the present study

Research Setting and Participants

A survey was given to EFL student teachers in Indonesian universities. The survey was undertaken in order to collect rich data from the participants depicting their PUT, ISE, PEUT, and SRL. The participants represented three-and four-year student teachers of teacher education programs where their curriculum includes courses integrating technology-mediated language learning. They met the specified criteria, possessing experiences of technological tools, such as Google Classroom, Edmodo, institutional e-learning platform, Zoom, Google Meet, TED Talk, podcast, YouTube, WhatsApp, Facebook, and some language learning applications and exposure to English language skills. The number of students polled corresponds to Tinsley and Tinsley's (1987) idea that the number of subjects should be 5-10 times that of question items to persuade the reliability of factor analysis.

Research Instrument

After document analysis, the questionnaire was modified from the relevant studies (Davis, 1989; Tsai et al., 2011; Mei, Brown, & Teo, 2018; Zheng, et al., 2018) to create a questionnaire that is purposely to measure the variables of the current study— PUT, ISE, PEUT, and SRL A validation session with three experts or educators was then held to address construct and content validity evidence. After the qualitative process, statistical calculations were made to confirm the validity and reliability of the instrument at the time the SEM analysis was carried out. In the end, a questionnaire utilizing a five-point scale, ranging from 1 to 5 (representing strongly disagree to strongly agree) was generated.

Table 1.
Questionnaire of PUT

Variables	Definition	Aspects	Items	Measurement scale
Perceived Usefulness of Technology (PUT)	Student teachers' perception that online learning could increase or enhance their learning performance	Interest and learning	3	a five-point scale
		Collaboration and communication	3	
		Information retrieval	2	
	Total		8	

Table 2.
Questionnaire of ISE

Variables	Definition	Aspects	Items	Measurement scale
Internet Self-efficacy (ISE)	Student teachers' perception of their ability to use the internet function or application in the internet based learning environment	Usage	2	a five-point scale
		Sharing	2	
		Communication	2	
		Verification	2	
		Metacognition	2	
		Application	2	
		Learning	3	
	Total		15	

Table 3.
Questionnaire of PEUT

Variables	Definition	Aspects	Items	Measurement scale
Perceived ease of use of Technology (PEUT)	Student teachers' degree to which one believes that adopting a particular technology would be free of cognitive effort	Technology knowledge	2	a five-point scale
		Technology for Teaching	2	
		Technology for learning	4	
		Technology for social interaction	2	
	Total		10	

Table 4.
Questionnaire of SRL

Variables	Definition	Aspects	Items	Measurement scale
Self-Regulated learning (SRL)	Student teachers' online self-regulation refers to "the processes that learners use to activate and maintain cognitions, emotions, and behaviors to attain personal goals in online learning environment	Goal setting	2	a five-point scale
		Environment Structuring	2	
		Task Strategies	2	
		Time Management	2	
		Help seeking	2	
		Self-evaluation	2	
	Total		12	

Research Procedures

As introduced in the previous section, this study follows the steps of PLS Structural Equation Modelling. The following presents how the study was carried out when SMART PLS software was performed. There are five steps of implementing PLS SEM adapting Hair et al., (2014), as follows:

a. ***Specification of the model***

The model specification step is concerned with the inner and outer models' configuration. The inner model, also known as the structural model, displays the relationship between the constructs being evaluated. The outer models, also known as the measurement models, are used to evaluate the relationships between indicators and their construct. The model of this study is constructed based on theories and previous studies which proposes perceived usefulness (PU), internet self-efficacy (ISE), and perceived ease of use (PEUT) as exogenous variables, and self-regulated learning (SRL) as endogenous variables.

Exogenous variables are demonstrated by the arrows pointing to endogenous variables. While, endogenous variables are indicated by the arrows pointing towards them (see figure 2). Thus, the path model depicts the hypotheses and display variables relationships that will be examined.

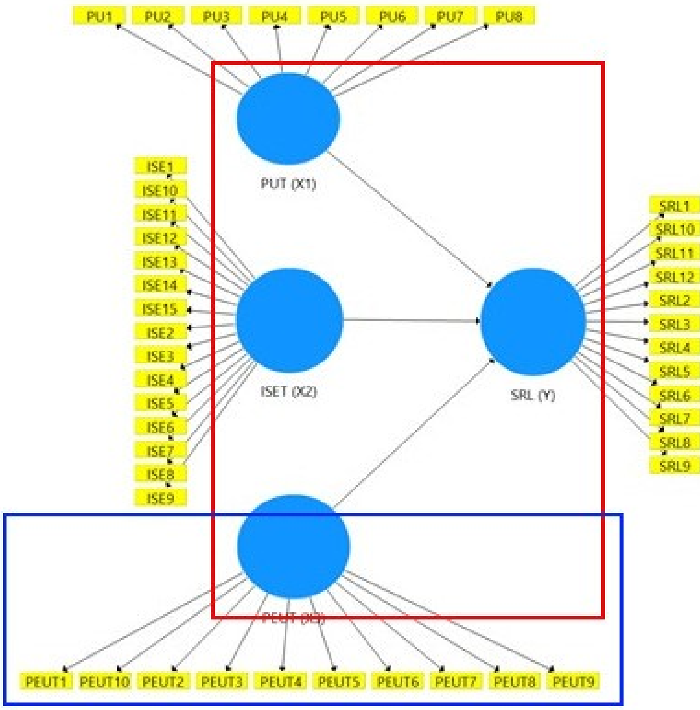

Figure 2. Specification of inner and outer models (or path model)

As seen in the model, the variables in ellipses (PUT, ISE, and PEUT) were viewed as latent variables which are the theoretical constructs of interest in the model. The rectangles are the manifest variables, which are the variables that were actually measured by the researcher. Each latent variable ideally was measured by several instruments. The scores obtained from each instrument represents a manifest variable that was conceptually related to one of the latent variables.

In Figure 2 the latent variable of perceived usefulness of technology (PUT) is represented by three manifest variables or indicators: interest and learning, collaboration and communication, and information retrieval. Latent variable of internet self-efficacy (ISE) was represented by seven manifest variables or indicators: usage (Us), sharing (S), communication (C), verification (V), metacognition (M), application (A), and learning (L). Latent variables of perceived ease of use of technology (PEUT) was represented by four indicators variable: technology knowledge (TK), technology for teaching (TT), technology for learning (TL), and technology for social interaction (TSI). Latent variable of self-regulated learning (SRL) was represented by six indicators variable: goal setting (GS), environment (ES) structuring, task strategies (TS), time management (TM), help-seeking, (HS) and self-evaluation (SE). The relevant theories and findings of previous studies become the bases that this model was constructed. The model shows a reflective approach, with the arrows leading from the construct to the indicators.

b. ***Data Collection and Examination***

The validated questionnaire was used to collect data given to the respondents online (using Google form). 45 items-questionnaire measures the student teachers' ISE, PUT, PEUT, and SRL. The present study administered a five-Likert Scale questionnaire to 365 respondents representing Indonesian university student teachers. Once the data are error, then they were removed from the analysis.

c. ***Path Model Estimation***

In this step PLS SEM was performed to estimate the relationships between the outer model, as known as measurement model (i.e., the loadings and weights) and inner model, also known as the structural model (i.e., path coefficient). Understanding data is critical at this step-in order to execute the algorithm. A data set or data matrix is created from construct indicators as survey replies.

d. Assessing Reflective Measurement Model

The reflecting measurement model was performed to determine composite reliability, that is to evaluate internal consistency, individual indicator reliability, and average variance extracted (AVE) to determine convergent validity.

e. ***Assessing Reflective Structural Model***

Once the measurement model was proven to be valid and reliable, the structural model was evaluated, following the five steps: finding collinearity to describe a relationship among latent variables and determining whether the strength of prediction is good or not, path coefficients that represent the hypothesized relationship among the constructs, coefficient determination (R^2 values) which measure the accuracy of the model and the value of squared correlation between a specific endogenous construct's actual and predicted values, effects size (f^2) to evaluate whether including or excluding the specified exogenous construct has substantive impact on the endogenous constructs or not by seeing the change of its R^2, and Blinfolding and predictive relevance (Q^2) to evaluate the magnitude of R^2 values, and GoF.

Data Analysis

The questionnaire data was analyzed using SMART PLS as the alternative model of structural equation model. This software does not need to see whether the data have normal or not normal distribution. It may be used to measure whether there is or not correlation of between two or more latent variables.

The analysis is conducted with two stages: reflective measurement of outer model to see the relationship between the indicators building latent variables and reflective measurement of inner model or structural model to see the relationship among latent variables within the model.

Measurement of Outer Model

Convergent and discriminant validity are used to evaluate measurement model. Convergent validity refers to principles that measurement of manifesto variables of a construct must have high correlation. This test is very important to see composite reliability as shown by loading factors demonstrating internal consistency reliability. To establish convergent validity, it does not only consider the outer loadings of the indicators but the average variance extracted (AVE) as well. AVE is defined as the grand mean value of the squared loadings of the indicators associated with the constructs (i.e., the sum of the squared loadings divided by the number of indicators). This study uses AVE more than 0.50 (>0.50). Thus, an AVE of less than 0.50 (<0.50) indicates that, on average, more error remains in the items than the variance explained by the construct (Hair et al., 2014).

Discriminant validity refers to the principles that the different manifesto of variable construct must not have correlation. Thus, establishing discriminant validity implies that a construct is unique and captures phenomena not represented by other constructs in the model (Hair et al., 2014). In this study, cross loading correlation uses more than 0.70 (> 0.70), and then, Fornell-Larker was used to compare the square root of the AVE values with the latent variable correlations. Specifically, the square root of each construct's AVE should be greater than its highest correlation with any other construct (Hair et al., 2014).

Cronbach's alpha (>0.70) are used to have an estimate of the reliability based on the intercorrelations of the observed variables. Cronbach's alpha assumes that all indicators are equally reliable (i.e., all the indicators have equal outer loadings on the construct). The loading factor is significant if the value (> 0.70), indicating the value is over error variance. The low loading factor (< 0.70) will be dropped because it is lower than the error variance (Hair et al., 2014).

High outer loadings on a construct indicate that the associated indicators have much in common, which is captured by the construct. This characteristic is also commonly called indicator reliability (or individual indicator reliability). At a minimum, all indicators' outer loadings should be statistically significant. Because a significant outer loading could still be fairly weak, a common rule of thumb is that the (standardized) outer loadings should be 0. 708 or higher (Hair et al., 2014).

Table 5.
Rule of thumb convergent and discriminant validity of outer model

Validity	Parameter	Rule of Thumb
Convergent Validity	Loading Factor	• >0.70 for confirmatory research • >0.60 for exploratory research
	Composite reliability	• >0.70 for confirmatory research • >0.50 for exploratory research
	AVE	• >0.50 for confirmatory and exploratory researches
Discriminant Validity	Cross loading	• >0.70 for the all variables
	Fornell-Larker Criterion	• >0.70 for intercorrelation of latent constructs

Measurement of Inner or Structural Model

In this phase, there are six steps: evaluation to collinearity assessment, structural mode path coefficients, coefficient of Determination (R^2 value), Effect size (f^2), and Blindfolding and Predicative Relevance (Q^2), and Goodness of Fit (GoF).

First, measurement of structural model needs to find the collinearity to describe a relationship among latent variables and to show whether the strength of prediction is good or not. Collinearity test can be through tolerance measurement (TOL) and Variance Inflation Factor (VIF) measurement. If VIF value is higher than 5 (VIF >5), the variable should be removed from the measurement. Second, the next measurement is to find significance estimation (path coefficients) which describe contribution or influence among construct variables. To this point, bootstrapping procedure is used and the value of significance is stated in t statistical test two-tailed with 0.5%. In mediator analysis with Smart PLS, bootstrap procedure is used to see the direct effect, indirect effect, and total effect (Hair et al., 2014). Path coefficients represent the hypothesized relationship among the constructs. They have standardized values between -1 and +1. Estimated path coefficients close to +1 represents strong positive relationships that are most always statistically significant. The closer the estimated coefficients are to 0, the weaker the relationships. Very low values close to 0 are usually nonsignificant**.** Third, the most commonly used to measure the structural model is the coefficient of determination (R^2 value). The coefficient values can depict the strength of predication of exogen to endogen variables of the structural model. The R- square (R^2) is produced by linier regression test. Hair et al., (2014) stated that 0.75 (very strong), 0.5 (moderate), and 0.25 (weak). Fourth, the next measurement is to find F^2 effect size that can be figured out when the change in the R^2 value that is when a specific exogenous construct is omitted from the model can be used to evaluate whether the omitted constructs has a substantive impact on the endogenous constructs. The impact could be categorized as 0.02 (weak) 0.15 (medium), 0.35 (strong), and less than 0.02 (no impact) (Hair et al., (2014). The last, procedure blindfolding will measure predictive path model. Predictive relevance (Q^2) is mostly called as predictive sample reuse which is used to validate endogen constructs (Goodness of Fit Model). The Q^2 value of endogen variable is good (fit model) if the value more than exogenous variables have. The categories are 0.02 (weak), 0.15 (moderate), and 0.35 (strong) (Hair et al., 2014).

FINDINGS

As the result of structural equation model (SEM) analysis, the findings are presented in terms of hypothesis analyses and model measurement, as follows:

Hypotheses Analyses

The three hypotheses were tested using SMART PLS SEM. Bootstrapping was used to determine path coefficients that demonstrate the causal relationship between the variables associated whether significant or not, including the path, whether positive or negative.

Perceived Usefulness of Technology and Self-Regulated Learning

Based on the hypothesis testing result, a path coefficient value was 0.167, and P value was 0.087 (with α 0.05). It indicates that PUT does not significantly influences SRL but has positive influence. In other words, PUT does not drive learners to demonstrate their self-regulation skills significantly; however, the path positive value indicates that the higher PU will drive the higher SRL the student teachers can demonstrate.

Internet Self-Efficacy and Self-Regulated Learning

Based on the hypothesis testing result, a path coefficient value was 0.167 and P value was 0.013 (with α 0.05). It indicates that ISE significantly and positively influences SRL in which ISE is able to accommodate student teachers to demonstrate their metacognition and cognition skills and motivation as well in their learning experiences.

Perceived Ease of Use of Technology and Self-Regulated Learning

Based on the hypothesis testing result, a path coefficient value was 0.418 and P value was 0.000 (with α 0.05). It indicates that PEUT significantly and positively influences SRL. In other words, PEUT drives learners to easily demonstrate their self-regulation skills such as: goal setting, environmental structuring, task strategies, time management, help-seeking, and self-evaluation in their learning experiences (i.e., SRL). When compared to other variables, PEUT of student teachers has the highest influence on their SRL, with a coefficient value of 0.418. They are motivated to be able to greatly control their learning since they believe technology to be easy to use.

Measurement Model Analysis

In this measurement model analysis, PLS SEM was used to evaluate the reliability and validity of the constructs measures. For the validity purpose, convergent validity and discriminant validity assessment were carried out. According to Hair et al. (2014). There are two criteria to measure whether the outer model meets with convergent validity requirement for reflective construct: loading factor (>0.70) and AVE (>0.50). Based on the loading factors validity test as shown in Table 6 and Figure 3 below, it is known that the entire loading values of manifesto variables or indicators of each construct is greater than 0.70, indicating that it has fulfilled the validity standard based on the loading value. While average variance extracted (AVE) is more than 0.50.

Table 6.
Construct Validity and Convergent validity

Indicators	Questionnaire items	Factors loadings	Composite Reliability (CR)	Average Variance Extracted (AVE)	Cronbach Alpha
Perceived Usefulness	PU1	0.902	0.957	0.737	0.949
	PU2	0.889			
	PU3	0.868			
	PU4	0.830			
	PU5	0.799			
	PU6	0.889			

	PU7	0.833			
	PU8	0.851			
Internet Self-Efficacy	ISE1	0.860	0.973	0.709	0.970
	ISE2	0.860			
	ISE3	0.885			
	ISE4	0.847			
	ISE5	0.841			
	ISE6	0.757			
	ISE7	0.829			
	ISE8	0.865			
	ISE9	0.891			
	ISE10	0.877			
	ISE11	0.719			
	ISE12	0.800			
	ISE13	0.863			
	ISE14	0.863			
	ISE15	0.856			
Perceived ease of Use	PEU1	0.777	0.956	0.684	0.949
	PEU2	0.830			
	PEU3	0.844			
	PEU4	0.793			
	PEU5	0.778			
	PEU6	0,792			
	PEU7	0,883			
	PEU8	0,874			
	PEU9	0,850			
	PEU10	0,839			
Self-Regulated Learning	SRL1	0.877	0.958	0.654	0.952
	SRL2	0,847			
	SRL3	0.792			
	SRL4	0.722			
	SRL5	0.756			
	SRL6	0.782			
	SRL7	0.829			
	SRL8	0.848			
	SRL9	0.802			
	SRL10	0.772			
	SRL11	0.829			
	SRL12	0.833			

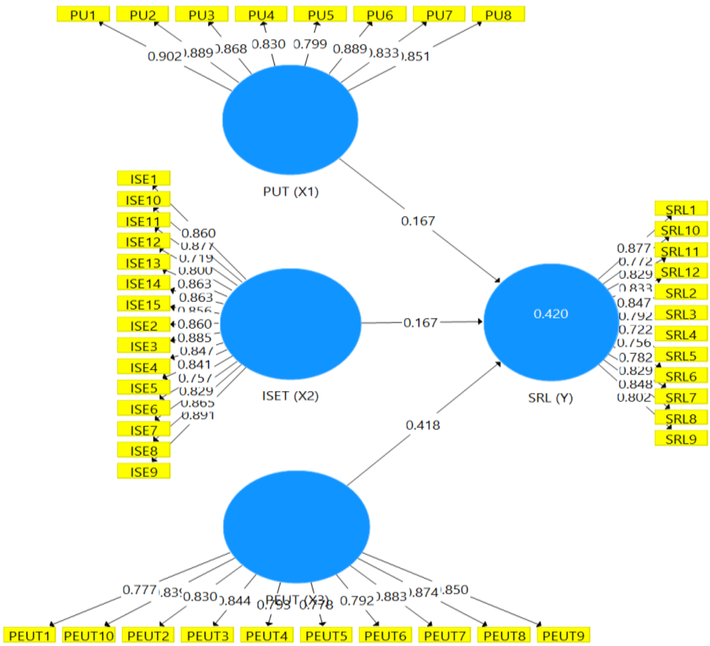

Figure 3. Validity Testing based on Loading Factors

To see whether different manifesto of variable construct does not have correlation and the construct is unique and captures phenomena not represented by other constructs in the model (Hair et al., 2014), discriminant validity was performed. To this respects, the value of cross loading and the square root of AVE of each constructs must be figured out (Hair et al., 2014). The result shows that cross loading of each construct is more than 0.70 (> 0.70). Meanwhile, the result of Fornell-Larker demonstrates that the square root of the AVE values with the latent variable correlations is greater than its highest correlation with any other construct. In discriminant validity testing, the value of the square root of the AVE of a latent variable is compared with the correlation value between the latent variable and other latent variables. It is known that the square root value of AVE (0.842, 0.827, 0.858, and 0.809) for each latent variable is greater than the highest correlation values with any other constructs. It is concluded that it has met the requirement of discriminant validity. (See Table 7)

Table 7.
Discriminant Validity testing

Variables	ISET (X2)	PEUT (X3)	PUT (X1)	SRL (Y)
ISET (X2)	0,842			
PEUT (X3)	0,547	0,827		
PUT (X1)	0,526	0,596	0,858	
SRL (Y)	0,484	0,609	0,504	0,809

To see internal reliability of each construct, Cronbach Alpha and composite reliability assessment were accomplished. As shown in table 6 the Cronbach alpha scores shows that the reliability of constructs ranged from 0.949 to 0.970 (>0.70); and, the AVE values ranged from 0.654 to 0.737, more than the cut-off value (>0.50), indicating the values are greater than the variance.

Structural Model Analysis

In evaluating structural model or inner model there are six steps passed through to acquire collinearity assessment (VIF), structural mode path coefficients, coefficient of Determination (R^2 value), Effect size (f^2), and Goodness of Fit (GoF).

Collinearity

Collinearity test was performed to see whether there is a strong correlation between independent variables in the model. If inner model Collinearity is indicated, the construct variables must be excluded from the model. In other words, If VIF value is higher than 5 (VIF >5), the variable should be removed from the measurement. The collinearity test can be through tolerance measurement (TOL) or Variance Inflation Factor (VIF) measurement. Using PLS Algorithm, VIF values can be acquired as shown in table 8. The result shows all

Inner VIF values are less than 5 (<5). This means there is no Collinearity within the model.

Table 8.
Collinearity statistics (VIF)

	ISET (X2)	PEUT (X3)	PUT (X1)	SRL (Y)
ISET (X2)				**1,565**
PEUT (X3)				**1,755**
PUT (X1)				**1,700**
SRL (Y)				

Path Coefficients Analysis

Bootstrapping procedure was used and the value of significance is stated in t statistical test two-tailed with 0.5%. The result shows that the all path coefficients are less than 0.05 ($p<0.05$). This indicates that the variable constructs significantly and positively influence the other constructs within the model as well as the all $t_{statistics}$ are greater than t_{table} (1.96).

Table 9.
Structural model: Path Coefficients–Bootstrapping

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
ISE -> SRL	0.167	0.167	0.067	2.506	0.013
PEUT -> SRL	0.418	0.429	0.106	3.930	0.000
PUT -> SRL	0.167	0.158	0.097	1.717	0.087

Through bootstrapping, direct effect values can be acquired as shown in table 9. This means that ISET and PEUT significantly and positively influence SRL. It can be seen from $p<0.05$ and all $t_{statistics}$ are greater than t_{table} (1.96). Meanwhile, PUT has positive direction on SRL but has not significant influence.

Coefficient of determination of R-squared (R^2)

Coefficient of determination (R^2 value) was performed to measure the strength of predication of exogenous to endogen variables of the structural model. The R- square (R^2) is produced by linier regression test. Hair et al., (2014) stated that 0.75 (very strong), 0.5 (moderate), and 0.25 (weak). Using the PLS Algorithm, it is acquired that SRL (0.420). It means SRL can be explained 42% by PUT, ISE, and PEUT. (see Table 10)

Table 10.
R square (R^2)

	R Square	**Interpretation**
SRL (Y)	0,420	Moderate

Effect Size (f^2)

F^2 effect size measurement was conducted to figure out when the change in the R^2 value, that is when a specific exogenous construct is omitted from the model, can be used to evaluate whether the omitted constructs has a substantive impact on the endogenous constructs. The impact could be categorized as 0.02 (weak) 0.15 (medium), 0.35 (strong), and less than 0.02 (no impact) according to Hair et al., (2014). Based on the result, the influence of PU → SRL is 0.127 (medium); PU → PK is 0.142 (medium); ISE→SRL is 0.096 (weak); ISE → PK is 0.070 (weak); SRL → PK is 0.176 (medium). (see Table 11)

Table 11.
Square (f^2)

Variables	**F^2**	**Interpretation**
PUT →SRL	0.028	weak
ISE →SRL	0.031	weak
PEUT→SRL	0.172	medium

Goodness of Fit model

Goodness of Fit assessment is performed to see whether the model built or proposed is fit or not. Using PLS Algorithm, the values are acquired.

Table 12.
Model of Fit

	Estimated Model
SRMR	0.054
NFI	0.802

Seeing the table above, standardized root mean square residual (SRMR) estimated model (0.054) is less than 0.10 or 0.08. This means the model is fit. Besides, Normed Fit Index (NFI) values (0.8) which is greater than or equal to 0.8, shows the model fit (Henseler et al., 2016). The closer the NFI to 1, the better the fit. The representative fit measures accomplishment by SRMS and NFI can assess that the model proposed is fit.

DISCUSSION

Technology integration in education has an important role in emerging effective educational process and improving teaching and learning (Chuang, Weng, &Huang, 2015; Yurkofsky, Blum-Smith & Brennan, 2019). This practically promotes that technology acceptance is quite important which can predict whether the student teachers will accept or reject the emerging technology. In other words, technology acceptance measurement is the way to determine the student teachers' intention toward using new technology in their educational practice. Technology mediated language learning necessitates learners' confidence in performing technology-aided action and their self-control skill (Sun & Rueda, 2012; Tsai et al., 2011) and enables learners to get engaged with others as well as stimulates them to be able to regulate their learning and do self-monitoring of their own learning (Sun & Rueda, 2012).

A study (Broadbent & Poon, 2015) proved that SRL techniques, particularly cognition and metacognition, and critical thinking were strongly related to technological academic accomplishment. It means that the learners may benefit from technological learning environment that fosters learning autonomy and successfully engages them in their learning process (Wang et al., 2013). This makes sense since self-regulated learners are individuals who are critically set their own goals, use appropriate approaches, and undertake assessment for themselves when digital classroom occurs (Zheng et al., 2018).

Due to the first hypothesis testing result, a path coefficient value was 0.167, and P value was 0.087 (with α 0.05), it specifies that PUT does not significantly influences SRL. However, the path positive value suggests that the greater the PU, the greater the SRL that the student teachers are able to demonstrate. It is expected that maximizing the PUT indicators of interest and learning, collaboration and communication, and information retrieval in technological learning environment will have a major impact on SRL by changing the p value. The relevant studies confirm that technology (e.g., e-learning, application, social media, web-based learning) gives usefulness in enhancing learning experiences and the learners are able to organize and rehearse learning content to be learned and monitor their learning processes (Artino & Stephens, 2009), develop their goal orientation, self-efficacy belief (Sharma et al., 2007), and self-management (Tsai, et al., 2011; Sun & Rueda, 2012), online help-seeking (Liu, 2017), and environmental structuring. It is no doubt since technology deployment occurs in the classroom, it drives learners to actively and confidently govern their learning by engaging their cognitive and metacognitive skills and preserving their motivation.

Based on the second hypothesis testing result, a path coefficient value was 0.167, and P value was 0.013 (with α 0.05). This indicates that ISE significantly influences SRL since learners with high internet self-efficacy are more likely to have information searching skills (Rains, 2008; Tsai & Tsai, 2003). Learners with high level of ISE will favor digital technology that allow them to utilize the internet to access several sources and extend information through learning activities (Liang & Tsai, 2008). This situation is consistent with a study that found that L2 language learners have demonstrated better self-regulation capacity in digital setting in terms of setting goals, managing time, structuring learning environmental, seeking assistance, task strategies, and self-assessment because they have positive attitude towards language learning as well as intrinsic interest (Zheng et al., (2018).

The last, based on the third hypothesis testing result, a path coefficient value was 0.418 and P value was 0.000 (with α 0.05). It indicates that PEUT significantly and positively influences self-regulated learning. In other words, PEUT drives learners to easily demonstrate their self-regulation. P**erceived ease of use** can be identified when technology facilitates users to use technology to perform their certain behaviors (i.e. learning behavior) without little requirement or no effort. For instance, in order to effectively manage their own learning, students in online learning environments must feel comfortable using technology. Tsai et al. (2011); Sun & Rueda, 2012) Alternatively, students will incorporate technology into their learning when it is simple to use, web-accessible and mobile-accessible through internet connections, and produces results quickly (Yang & Wang, 2019). It implies that students who find technology easy to use are more likely to perform self-regulated learning, which allows them to create a learning environment that fits their time and pace.

CONCLUSION

This study uses SEM analysis to assess the causal relationships among the variables of PUT, ISE, PEUT, and SRL and learn the pattern of their relationship in order to identify a fit model. Based on the result of hypotheses examination, we can draw a conclusion that if technology-mediated learning is perceived positively by student teachers, they will use any technological resources to enhance their learning performances and attain the learning goals. Internet self-efficacy and perceived ease of use of technology, in particular, significantly influence self-regulated learning. It means that the use of technology properly in English learning may promote learning autonomy which drive them to critically and independently develop their metacognition, cognition, and motivation skills which develop problem solving skill in order to achieve the goals. In other words, assessing PUT, ISE, PEUT, and SRL using SEM analysis gives information about to what extent the student teachers' belief towards technology for educational purposes and their strength of strategy and intention to use technology which support their self-regulated learning. Alternatively, employing various technologies effectively within the learning environment will also impact specific facets of self-regulated learning.

Nevertheless, certain aspects were identified as limitations of this study, prompting the need for further investigation. This study solely concentrated on perceptions related to technology (PUT, ISE, PEUT) and self-regulated learning (SRL) within the context of language learning. Thus, language knowledge or skills could potentially become the primary focus for subsequent researchers to explore.

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