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## Exploring the factors affecting pre-service science teachers' actual use of technology during teaching practice

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The primary objective of the research reported on here was to decide whether a combined framework of the theory of planned behaviour (TPB) and technological pedagogical and content knowledge (TPACK) could be a valid and reliable model to predict Indonesian pre-service science teachers' (PSTs') actual use of technology (AUT) during teaching practice. A survey instrument consisting of attitudes (ATs), subjective norms (SN), perceived behavioural control (PBC), technological pedagogical knowledge (TPK), technological content knowledge (TCK), technological pedagogical content knowledge (TPCK), and AUT was adapted from previous studies and validated through face and content validity. Thereafter, the instrument was piloted to 135 PSTs and validated through exploratory factor analysis (EFA). The sample ( $n = 457$ ) completed the instrument during the main data collection. The data analysis was done through the steps of partial least square structural equation modelling (PLS-SEM), *t*-test, and analysis of variance (ANOVA). Through the measurement model phase, the combined framework was reported to be reliable and valid. SN was the strongest predictor ( $\beta = .445$ ) of AUT, followed by PBC ( $\beta = .281$ ). Meanwhile, AT, TPK, TCK, and TPCK were reported to be insignificant. Additionally, significant differences regarding AUT were reported based on gender and institution. An insignificant relationship emerged based on information and communication technology (ICT)-based courses.

**Keywords:** actual use of technology; Indonesia; pre-service science teachers; technological pedagogical and content knowledge; theory of planned behaviour

### Introduction

The use of technology has dynamically changed education. The change also emerged from teachers' perspectives towards the integration of technology into their teaching (Ertmer, 2005). Teachers' perspectives are predicted by their knowledge and beliefs (Ajzen, 1991; Mishra & Koehler, 2006). Studies on educational technology should continuously report on in different contexts and settings (Habibi, Yusop & Razak, 2020b; Hart & Laher, 2015). Technology, when integrated into education, could improve instruction. More studies are needed to inform that technology integration fosters learning processes and achievement, especially in developing countries. Teachers who recognise technology as a problem-solving tool for their instructional activities, change the way they teach. Technology integration is necessary in modern-day research due to its influence on the 21st-century generation, Millennials and Generation Z.

Two well-established frameworks in the educational technology field and research are technological, pedagogical and content knowledge (TPACK) and the theory of planned behaviour (TPB) (Ajzen, 1991; Mishra & Koehler, 2006). TPACK is a framework that combines the fundamental dynamics of instructional activities using technology (Mishra & Koehler, 2006). TPB is a widely used and validated theory relying on belief-based measurements to provide a comprehensive elaboration to understand the use of technology in a given engagement of behaviour (Sadaf, Newby & Ertmer, 2012).

Many combined-framework studies have been conducted in developed countries to examine the integration of technology in education, namely between the technology acceptance model (TAM) and TPACK (Joo, Park & Lim, 2018), TPB and TPACK (Taimalu & Luik, 2019), TAM and expectation confirmation theory (Mohammadi, 2015), and TAM and TPB (Cheng, EWL 2019). However, a few studies were reported in developing countries (Fatima, Ghandforoush, Khan & Di Mascio, 2019). Therefore, the main objective with this research was to decide whether the combined framework of TPB and TPACK could be a valid and reliable model to predict PSTs' AUT during teaching practice. The predicting power of both TPACK and TPB constructs to AUT was also elaborated on. The significant differences regarding AUT were also reported based on gender, major subject, and institution.

This study would contribute to a guidance model for national and international researchers interested in doing research with a similar topic within different contexts and settings.

#### Literature Review

Technology integration challenges during teaching practice are probably more pronounced when young teachers, including pre-service science teachers (PSTs) start teaching as beginners (Ertmer, 2005; Habibi, Razak, Yusop, Mukminin & Yaqin, 2020). The challenges might occur due to their senior co-workers' and tutors' unrealistic expectations in their schools. The PSTs' skills and capacities are expected to help the seniors in integrating technology in teaching (Ertmer, Ottenbreit-Leftwich, Sadik, Sendurur & Sendurur, 2012). It is certain that the use of technology falls within PSTs' comfort zones, as they use technology for social networking, entertainment, communication, and information (Ertmer et al., 2012). However, most have little knowledge and experience of integrating technology into teaching (Graham, Borup & Smith, 2012; Habibi et al., 2020b).

#### Technology adoption in science education

In general, technology supports instruction in four aspects: "active engagement, collaborative learning, real-world contexts, and frequent and immediate feedback" (Roschelle, Abrahamson & Penuel, 2004:253). Wang, Kinzie, McGuire and Pan (2010:382) inform that technology might also provide students with "high-order thinking and metacognitive skills" for meaningful learning. In science education, technology was reported to

support science learning by establishing students' motivation and interest in science education, such as engaging students for real data analysis in citizen science projects (Price & Lee 2013); facilitating them to information, such as scientific data (Adams 2011; Bailey, Pomeroy, Shipp, Shupla, Slater, Slater & Stork, 2011); scaffolding learning with strategic support (Wang et al., 2010); and using computer simulation in learning science (Wang et al., 2010). These dimensions help science education change. In a study conducted among high school students, Adams (2011) used real-time data (RTD) to examine predictions on an aquatic ecosystem. The RTD developed the students' comprehension of factors affecting tidal creeks. In this context, Adams (2011) highlighted that technology could help teachers to improve students' interest in science through knowledge of science.

#### Combined frameworks in educational technology research

Many combined frameworks have been established to help evaluate technology integration in education (Table 1). EWL Cheng (2019) combined TAM and TPB to elaborate factors predicting students' intentions to implement wikis in their learning. The study reported that ATs, SNs, and PBC significantly predict students' intention of using wikis. In addition, Mohammadi (2015) adapted TAM and expectation confirmation theory reporting SN as the stronger predictor to the use of technology in education. In our study (see Figure 1), we combined TPACK (Mishra & Koehler, 2006) and TPB (Ajzen, 1991).

**Table 1** Prior studies of combined frameworks in educational technology research

Authors	Sample	Method	Integrated framework
EWL Cheng (2019)	174 students of a university in Hong Kong	Path analysis (PLS-SEM)	TPB and TAM
Joo et al. (2018)	296 Korean PSTs	Path analysis covariance-based structural equation modelling (CB-SEM)	TPACK and TAM
Mohammadi (2015)	390 students from Tehran	Path analysis (PLS-SEM)	TAM and expectation confirmation theory
Sánchez-Prieto, Huang, Olmos-Migueláñez, García-Peñalvo & Teo (2019)	222 response	Path analysis (PLS-SEM)	TAM and new model
Taimalu & Luik (2019)	54 teacher educators	Path analysis (CB-SEM)	Knowledge and beliefs
Teo, Sang, Mei & Hoi (2019)	464 PSTs in China	Path analysis (CB-SEM)	TAM & TPACK

#### Theory of planned behaviour

TPB is a technology adoption framework that relies on belief-based measurements to understand the intention or use of technology (Ajzen, 1991). The theory is an extension of the theory of reasoned action (TRA) founded by Fishbein and Ajzen (1975). TRA refers to the rational decision for a

teacher's intention to use or the actual use based on personal and social factors. The personal factor or AT refers to a teacher's beliefs on the use of technology in providing supportive outputs. The social factor or SN represents teachers' perception of others' in predicting AUT. Additionally, it reflects that the behavioural intention to use

technologies is more significant if a teacher possesses control of the integration or PBC. Many educational researchers have used TPB as a framework to study teachers' AUT (e.g., Sadaf et al., 2012; Teo & Lee, 2010; Teo & Van Schaik, 2012).

#### *TPB components*

Some studies have reported AT to be a significant factor predicting the intention to use or the actual use of ICT in teaching (Cheng, EWL 2019; Fatima et al., 2019; Lung-Guang, 2019; Salleh, 2016; Teo & Van Schaik, 2012). AT was detected to be the most significant factor ( $\beta = 0.675$ ) in predicting intention to use technology (Salleh, 2016). It was also reported to be the most significant in predicting interactive simulation in South Africa (Kriek & Stols, 2010). Similarly, Teo and Van Schaik (2012) had the same research result; AT being the best predictor ( $\beta = 0.675$ ) with SN and PBC being minor predictors. Based on these studies, AT was included as part of the TPB framework to predict AUT.

*H<sub>1</sub>*: AT will have a significant effect on AUT.

Many studies report that SN predicts the use of technology in education (Cheng, EWL 2019; Fatima et al., 2019; Kreijn, Van Acker, Vermeulen & Van Buuren, 2013; Lung-Guang, 2019; Teo & Van Schaik, 2012). Fatima et al. (2019) indicated that SN had a stronger correlation ( $\beta = 0.348$ ) with the intention to use ICT than AT and PBC. EWL Cheng (2019), Kreijn et al. (2013), and Teo and Van Schaik (2012) have also reported that SN was a predictor of AUT. Therefore, SN is considered as an important factor to predict PSTs' AUT during teaching practice.

*H<sub>2</sub>*: SN will have a significant effect on AUT.

Some researchers have also studied PBC (Cheng, EWL 2019; Fatima et al., 2019; Lung-Guang, 2019; Salleh, 2016; Teo & Van Schaik, 2012), which has been reported to be the strongest predictor ( $\beta = 0.561$ ) in a study involving TPB as the framework (Lung-Guang, 2019). Fatima et al. (2019) also reported PBC to predict ( $\beta = 0.239$ ) the use of mobile learning (m-learning) in a Malaysian PST training programme. Similar results were also achieved by other researchers (Cheng, EWL 2019; Salleh, 2016; Teo & Van Schaik, 2012).

*H<sub>3</sub>*: PBC will have a significant effect on AUT.

#### *Technological pedagogical and content knowledge (TPACK)*

TPACK was first introduced as a framework for effective technology integration into teaching (Mishra & Koehler, 2006). The proper way for the integration in TPACK requires educators to formulate the interaction of three TPACK components: technology, pedagogy, and content. Although the components seem to represent distinct knowledge bases, the interaction between the core components include the essence of TPACK.

TPACK comprises of seven bases; three knowledge bases and four interacted bases. Technological knowledge (TK) is about how to use different technologies; pedagogical knowledge (PK) is on different teaching and learning approaches and theories of learning; content knowledge (CK) is subject matter knowledge; pedagogical content knowledge (PCK) is a combination of CK and PK to make the content more understandable; TCK is knowledge of how ICT is used by content experts; TPK is how to use appropriate technology to support instruction without considering the subject matter; and TPCK is knowledge of how to use appropriate pedagogical approaches for certain content with appropriate technology (Mishra & Koehler, 2006).

#### *TPACK components*

TPACK components positively predict other variables, including the use of technology in teaching (Aslan & Zhu, 2017; Joo et al., 2018; Mei, Brown & Teo, 2018; Taimalu & Luik, 2019; Teo et al., 2019). A report from Mei et al. (2018) informed that TPACK was a significant predictor for the intention to use Web 2.0 in the English as a foreign language (EFL) context among Chinese teachers ( $\beta = .180$ ). Aslan and Zhu (2017) also revealed that PK was significant in predicting AUT in teaching practice in Turkey ( $\beta = .330$ ). Teo et al. (2019) reported TPACK's significance to predict the intention to use Web 2.0 in China ( $\beta = .260$ ). Perceived PK was reported to be a significant factor for perceived technology integration (Taimalu & Luik, 2019). However, in Joo et al.'s (2018) research with Korean pre-service teachers, no TPACK components were reported to be predictors of the intention to use technology. In this study, we used three T-combined TPACK components; TPK, TCK, and TPCK, to examine AUT.

*H<sub>4</sub>*: TPK will have a significant effect on AUT.

*H<sub>5</sub>*: TCK will have a significant effect on AUT.

*H<sub>6</sub>*: TPCK will have a significant effect on AUT.

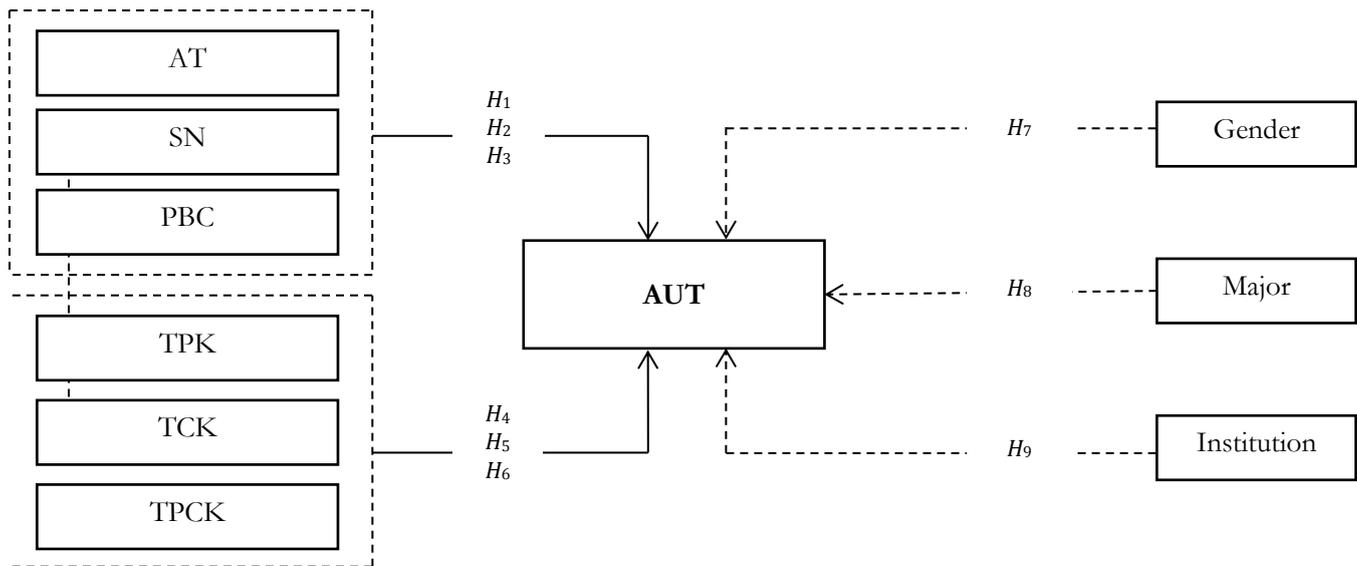
#### *Demographic information*

In our study we also evaluated the roles of demographic information on gender, age, and institution to understand the differences regarding AUT. Some studies (e.g., Aslan & Zhu, 2017; Kolodziejczyk, 2015; Sang, Valcke, Van Braak & Tondeur, 2010; Teo et al., 2019) have reported the differences among demographic variables for AUT in education. Therefore, three hypotheses were submitted for this objective.

*H<sub>7</sub>*: There will be a significant difference regarding gender for AUT.

*H<sub>8</sub>*: There will be a significant difference regarding ICT-based courses for AUT.

*H<sub>9</sub>*: There will be a significant difference regarding institutions for AUT.



**Figure 1** Research model

### Method

In this study we employed a survey as method. The process started with the development of the survey instrument through the adaptation process. To build validity of the construct, we applied face and content validity, followed by a pilot study. EFA was done, whereafter the data analysis was conducted through steps of PLS-SEM, *t*-test, and ANOVA.

### Instrumentation

We adapted and constructed the instrument based on previous studies; TPB (Sadaf et al., 2012; Teo & Lee, 2010), TPACK (Koh, Chai & Tsai, 2010; Taimalu & Luik, 2019), and AUT (Aslan & Zhu, 2017). The adapted instrument was assessed for content and face validity, mainly using the content validity index (CVI) (Lynn, 1986). Five users were invited to discuss the instrument as part of the face validity process. Five experts in educational technology and policy were asked to assess the instrument (Habibi, Yusop & Razak, 2020a).

We distributed the instrument to 10 experts for CVI. All indicators were evaluated for their a) relevance, b) clarity, and c) simplicity rated on a 4-point scale (Lynn, 1986). The item level of CVI (I-CVI) and the scale level of CVI (S-CVI) were measured for the instrument. The I-CVI measurement was done by dividing the score of 3 or 4 by the total number of experts (Lynn, 1986). The I-CVI score should not be less than .78, with 10 experts involved. Similarly, the S-CVI score should not be less than .80 on a scale rated 3 or 4. We also calculated the modified kappa ( $k^*$ ) and the probability of chance ( $P_c$ ). All values of I-CVI, S-CVI,  $k^*$ , and  $P_c$  exceeded the threshold values.

The instrument was piloted with 135 PSTs. Thereafter, the EFA was done to examine five measurements; sphericity Bartlett test ( $p < .005$ ),

Kaiser-Meyer-Olkin (KMO,  $> .800$ ), factor loading  $\geq (.500)$ , communalities ( $> .300$ ), and eigenvalue ( $\geq 1.000$ ) (Hair, Black, Babin & Anderson, 2010). All indicators achieved the threshold values. The value of KMO was .901 and Bartlett's test of sphericity value was significant ( $p = .000$ ). All factor loading values exceeded .500, ranging from .561 to .864. The communality ranged from .474 to .787. The eigenvalue of all factors ranged from 1.203 to 7.577. In this EFA process, two indicators (TPK1 & AT1) were dropped since cross-loading values were highly detected.

Seven constructs were achieved through the EFA procedures resulting in 39 indicators. AT consisted of seven indicators (AT2, AT3, AT4, AT5, AT6, AT7 & AT8). Five indicators were included for both SN (SN1, SN2, SN3, SN4 & SN5) and PBC (PBC1, PBC2, PBC3, PBC4 & PBC5). Five indicators were included for TPCK (TPCK1, TPCK2, TPCK3, TPCK4 & TPCK5), two indicators for TCK (TCK1 & TCK2), and three indicators for TPK (TPK2, TPK3 & TPK4). Twelve indicators emerged for AUT (AUT1, AUT2, AUT3, AUT4, AUT5, AUT6, AUT7, AUT8, AUT9, AUT10, AUT11 & AUT12).

### Data Collection

We distributed the survey instrument to two Indonesian universities (institution A and institution B). Using printed material, data were collected from October 2018 to January 2019. All responses were entered into the Statistical Package for the Social Sciences (SPSS) for further analysis. The population of this research was around 1.2 million student teachers in 374 Indonesian pre-service teacher training programmes. The target population of this research included all Indonesian PSTs; the target population was separated based on the university for

stratified sampling. More than 500 printed sets of questionnaires were distributed of which 468 were returned. Data from 457 PSTs (377 females and 80 males) were measurable. Two hundred and thirty-eight PSTs were from institution A and 174 PSTs from institution B; we masked the university's original names as part of research ethics (Creswell, 2014). One hundred and thirty-three PSTs reported that they had never attended ICT-based courses; 224 PSTs attended one to three ICT-based courses. One hundred respondents indicated that they had attended ICT-based classes more than three times.

#### Data Analysis

Before analysing the main data by measuring the model and assessing the structural model, data preparation was conducted through SPSS. We aimed to ensure that the data did not include any issues regarding outliers, missing values, and non-normal distributions (Hair et al., 2010). The assessment of skewness and kurtosis, as well as q-q plot and histogram were conducted. No issues regarding outliers, missing values, and non-normal data distribution emerged.

In examining the reliability and validity of the model, four steps proposed by Hair, Risher, Sarstedt and Ringle (2019) were included; measuring the reflective indicator, internal consistency reliability, convergent validity, and discriminant validity. The assessment of the structural model involved some systematic examinations (Hair et al., 2019), such as collinearity, path coefficients ( $\beta$ ), coefficient of determination ( $R^2$ ), the effect size of  $f^2$ , and predictive relevance ( $Q^2$ ) (Hair et al., 2019). The significant differences regarding demographic information were analysed using *t*-test and ANOVA.

## Findings

### Measurement Model

The reliability and validity of the construct were examined in the measurement model (Hair et al., 2019). Table 2 shows the final results of all constructs for reflective indicators showing that all indicators achieved the recommended value of  $\geq .700$  (Hair et al., 2019). A few indicators produced values less than .700; AUT12 (.653), AUT1 (.656), AUT2 (.674), and AUT9 (.690) were subsequently eliminated (Hair et al., 2019). Cronbach's alpha and composite reliability (CR) values for most constructs were stable, below the maximum value of .950 and exceeding the minimum value of .708 (Hair et al., 2019). The least average variance extracted (AVE) value should be  $\geq .500$ , which explains 50% or more of the construct variance (Hair et al., 2019). All AVE values were above .500, ranging from .599 to .890.

In examining the discriminant validity, we reported the Fornell-Larcker criterion and Heterotrait-Monotrait (HTMT) values. The off-diagonal values shown in Table 3 are the correlations between the constructs, while diagonal values are square values of AVE, informing that the AVE value on its construct was greater than the values of the other constructs. The acceptable level of discriminant validity threshold was also obtained from HTMT value, which should be less than .900 (Hair et al., 2019). All HTMT values were below .850, suggesting that no issues emerged (Table 4). Based on the results of the measurement model (reflective indicator, internal consistency reliability, convergent validity, and discriminant validity), the proposed combined framework of TPB and TPACK to predict AUT among Indonesian PSTs during teaching practice was reported to be valid and reliable.

**Table 2** Loading, Cronbach's alpha, CR, and AVE

	Loading	Cronbach's alpha	CR	AVE
AT2	.780	.893	.916	.611
AT3	.790			
AT4	.844			
AT5	.831			
AT6	.740			
AT7	.748			
AT8	.732			
PBC1	.727	.847	.891	.620
PBC2	.786			
PBC3	.803			
PBC4	.833			
PBC5	.785			
SN1	.808	.870	.906	.658
SN2	.832			
SN3	.826			
SN4	.789			
SN5	.799			
TCK1	.964	.881	.942	.890
TCK2	.922			
TPACK1	.791	.833	.882	.599
TPACK2	.797			
TPACK3	.733			
TPACK4	.736			
TPACK5	.810			
TPK2	.821	.774	.869	.688
TPK3	.814			
TPK4	.853			
AUT10	.773	.879	.909	.625
AUT11	.713			
AUT5	.778			
AUT6	.843			
AUT7	.822			
AUT8	.806			

**Table 3** Fornell-Larcker criterion

	AT	AUT	PBC	SN	TCK	TPACK	TPK
AT	.782						
AUT	.589	.790					
PBC	.723	.647	.787				
SN	.677	.695	.687	.811			
TCK	.431	.366	.370	.420	.943		
TPACK	.574	.508	.548	.632	.547	.774	
TPK	.503	.425	.454	.527	.491	.710	.830

**Table 4** HTMT

	AT	AUT	PBC	SN	TCK	TPACK	TPK
AT							
AUT	.663						
PBC	.835	.741					
SN	.770	.789	.793				
TCK	.475	.404	.421	.470			
TPACK	.665	.590	.645	.742	.622		
TPK	.606	.511	.550	.643	.585	.881	

#### Assessment of the Structural Model

In the assessment of the structural model of the study we reported some statistical analyses, namely collinearity, path coefficients ( $\beta$ ), coefficient of determination ( $R^2$ ), the effect size of  $f^2$ , and predictive relevance ( $Q^2$ ).

#### Collinearity

The evaluation of the collinearity introduced the assessment of the structural model. The variance inflation factor (VIF) value of each predictor's construct is recommended to be lower than 3 (Hair et al., 2019). From the findings, the pairs of

predictors were evaluated for collinearity: AT, PBC, SN, TCK, TPACK, and TPK as predictors for AUT. The VIF value for AT as a predictor of AUT was 2.546, below the value of 3. Similarly, the other VIF values as the predictors of AUT were below 3; PBC (2.488), SN (2.492), TCK (2.506), TPACK (2.716), and TPK (2.130). As a result, no issues of collinearity emerged from this study.

#### Path coefficient

To assess the significant predicting relationship, we conducted bootstrapping, resampling 5,000 samples that assumed a 5% significance level. Two predictors were reported to be significant in predicting PSTs' AUT. SN was the strongest factor in predicting AUT ( $\beta = .424$ ;  $p < .001$ ) followed by PBC ( $\beta = .276$ ;  $p < .001$ ). Meanwhile, the other predictors (AT, TPK, TCK, and TPACK) were not statistically significant in predicting AUT (Table 5).

**Table 5** Bootstrapping result

<i>H</i>	Path	$\beta$	<i>t</i>	<i>p</i>	Significance
<i>H</i> <sub>1</sub>	AT → AUT	.070	1.083	.279	No
<i>H</i> <sub>2</sub>	SN → AUT	.424	7.643	.000**	Yes
<i>H</i> <sub>3</sub>	PBC → AUT	.276	4.362	.000**	Yes
<i>H</i> <sub>4</sub>	TPK → AUT	.004	.093	.926	No
<i>H</i> <sub>5</sub>	TCK → AUT	.042	.975	.329	No
<i>H</i> <sub>6</sub>	TPCK → AUT	.023	.377	.706	No

Note. \* $p < .005$ ; \*\* $p < .001$ .

#### *R*<sup>2</sup> value

The coefficient of determination (*R*<sup>2</sup>) aims to assess the model's predictive accuracy. It is the calculation of the squared correlation between a specific endogenous construct (Hair et al., 2019; Shmueli, Ray, Estrada & Chatla, 2016). *R*<sup>2</sup> values are in the range between 0 and 1; a higher value indicates a higher level of predictive accuracy. An *R*<sup>2</sup> value of .75 is considered substantial, while .50 is moderate, and .25 is weak (Hair et al., 2019). The *R*<sup>2</sup> value of the current model was .541, indicating a moderate result.

#### Effect size (*f*<sup>2</sup>)

The effect sizes (*f*<sup>2</sup>) measure the effect of a predictor construct on an endogenous construct. The *f*<sup>2</sup> examines the change in *R*<sup>2</sup> when a certain exogenous construct, or independent variable, is eliminated from the model. It is to assess the impact of an exogenous construct to the endogenous construct (Habibi et al., 2020b; Hair et al., 2019; Shmueli et al., 2016). A value of .02 is considered a small effect, .15 (medium effect), and .35 (large effect) (Hair et al., 2019). Only two effect sizes were detected in this study. The effect size of AT to AUT was medium (.157), while PBC to AT was small (.067). At the same time, the other effect sizes were not significant.

#### Predictive relevance (*Q*<sup>2</sup>)

The last stage of the process involved the predictive relevance of the model using Stone-Geisser's *Q*<sup>2</sup> value. When the model performs predictive relevance, the accuracy in predicting the data points of indicators in the model is accountable (Habibi et al., 2020b). Values greater than 0 indicate that the model's relevance for the construct is obtained; .02 as small, .15 as medium, and .35 as large. The procedure for achieving *Q*<sup>2</sup> values was processed through PLS-SEM's blindfolding (Hair et al., 2019). The value of *Q*<sup>2</sup> of this study was .313 (large).

#### Significance Differences Regarding AUT

Statistically significant differences were reported between gender ( $t = 1.529$ ;  $p < .005$ ) and institution ( $t = 7.320$ ;  $p < .001$ ) regarding Indonesian PSTs' AUT (Table 6). Female teachers' perceptions ( $M = 3.833$ ) were reported to be higher than that of male teachers ( $M = 3.718$ ). In addition, a significant mean value difference was also found between institution A ( $M = 3.955$ ) and institution B ( $M = 3.554$ ). Based on the ANOVA test informed by Table 7, an ICT-based course was not statistically correlated to AUT ( $F = .532$ ;  $p > .005$ ). The final model of this study is presented in Figure 2.

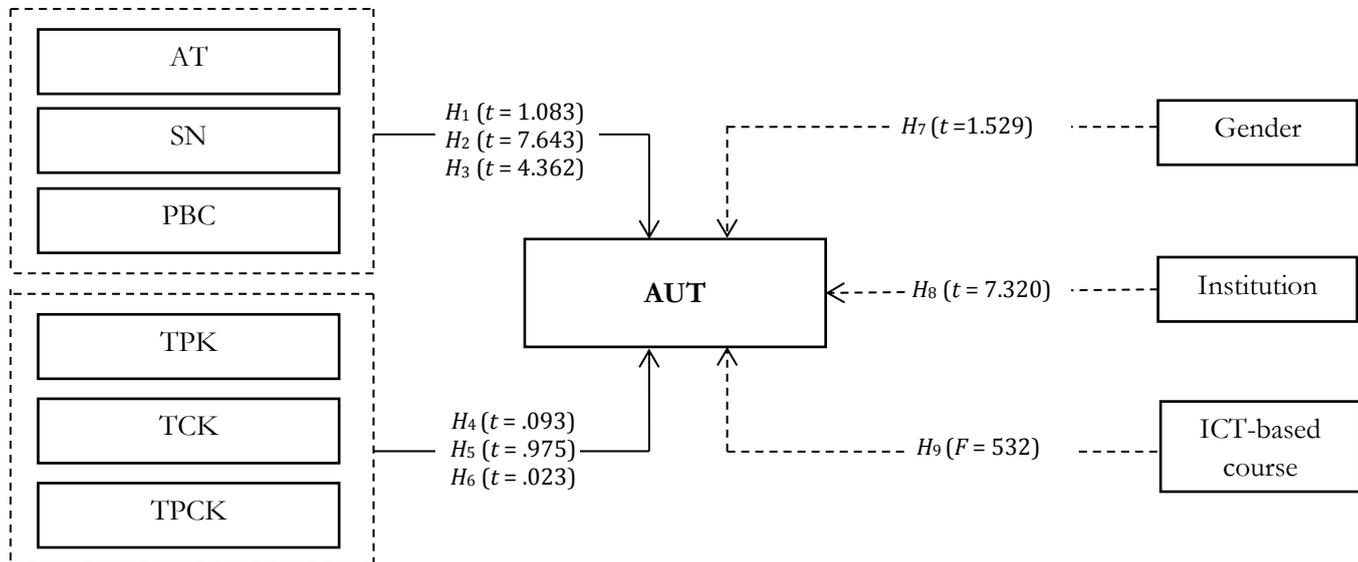
**Table 6** *T*-test

Demography	<i>n</i>	<i>M</i>	<i>t</i>	<i>p</i>	Significance
Gender					
Female	377	3.833	1.529	.017	*
Male	80	3.718			
Institution					
A	283	3.955	7.320	.000	**
B	174	3.554			

Note. \* $p < .05$ ; \*\* $p < .01$ .

**Table 7** ANOVA

Demography	<i>n</i>	<i>M</i>	<i>F</i>	<i>p</i>	Significance
ICT-based course					
0	133	3.758	.532	.588	No
1–3	224	3.818			
> 3	100	3.828			

**Figure 2** Final model

## Discussion

Through the measurement model in PLS-SEM, the combined framework of TPB and TPACK offered in this study has proven to be valid and reliable to predict Indonesian PSTs' AUT during teaching practice. The validation process can be a reference for future studies regarding factors predicting AUT among pre-service teachers, especially in developing countries. The validation process of combining two or more frameworks to predict the use of technology in education was also reported to be valid and reliable by previous studies in different contexts and settings (Koh et al., 2010; Kriek & Stols, 2010; Taimalu & Luik 2019). Therefore, the process is important for developing countries like Indonesia; academic research needs to verify its research context and setting as well as the culture of the respondents.

From the data analysis, two constructs, SN and PBC, were identified to be statistically significant in predicting AUT (Figure 2). SN was the strongest predictor. A similar result was also informed by Fatima et al. (2019), who did their study in Bangladesh. They reported SN as the strongest predictor for the use of m-learning. In addition to SN, PBC was also reported to be significant with a small effect size on AUT. The same result showed that PBC significantly predicted intention to use wikis in Hongkong (Cheng, SL & Xie, 2018) in a combined-framework study of TPB and TAM. Regarding TPB, Indonesian PSTs use technology devices on a daily basis. Thus, they have the ability to face the challenges regarding the technology used

in their teaching. Meanwhile, no TPACK constructs were reported to significantly predict AUT. This finding should be understood as a phenomenon to improve the training of TPACK for PSTs. The possible reason for these findings could be the lower level of TPACK of the PSTs in developing countries than that of TPB. The complex relationship of knowledge of technology, pedagogy, and content in teaching might trigger the insignificant in predicting powers.

A significant difference was detected in terms of gender with regard to AUT during teaching practice. Gender has also been considered in other studies regarding the intention to use ICT or actual use of ICT (Aslan & Zhu, 2017; Sang et al., 2010; Teo et al., 2019). In addition, a significant difference was also reported based on the institution regarding PSTs' AUT. Not many studies reported differences in terms of the institutions. However, Aslan and Zhu (2017) informed that there was a significant difference indicated in Turkish pre-service teacher's use of ICT in teaching. In contrast, our study revealed no significant difference in terms of ICT-based courses. The results of the analysis depict that gender and institution are determinant regarding technology integration among Indonesian PSTs. Female PSTs tend to have a good perspective on AUT, while the perspective of PSTs at institutions with low resources are low

## Conclusion

Nowadays, teachers' technology integration is unavoidable and complicated; therefore, the

exploration of factors predicting the integration should always be promoted. The current work has highlighted factors affecting actual use of technology in teaching. By focusing on PSTs and based on some previous studies, the combined framework of TPB and TPACK was proposed to predict Indonesian PSTs' actual use of technology. The model is valid and reliable and can benefit future researchers in studies with different contexts, settings, and technologies, especially those from developing countries.

When combined, TPB components (SN and PBC) significantly predict AUT. Subjective norm, which is defined as PSTs' perception of other people's influences, is the strongest predictor. This result might relate to the Indonesian culture and tradition in which other people, like those for other Asian countries, are appreciated and respected. In addition, PBC also positively predicted Indonesian PSTs' AUT, which might prove that the participants' perceptions of their ability to perform technology integration during their teaching practice controls their action in integrating technology. It might be triggered by their nature as millennials that are accustomed to the use of technology. On the other hand, all TPACK components included in this study were reported to be insignificant in predicting AUT. Therefore, the recommendation for educational stakeholders in developing countries like Indonesia is to focus more on the development of TPACK aspects in improving technology integration in education due to its complexity – especially for teaching practice.

From this study we also reported that the PSTs could gain technology integration during teaching practice differently in terms of gender and institutions. Therefore, the consideration of the different approaches for male and female teachers should be considered. An in-depth investigation should also be considered for technology integration in different institutions. Although not significant, the difference in terms of ICT-based courses should also be considered in fostering PSTs' competence for AUT during teaching practice. The findings require sustainable support to the research of technology integration in education. Supporting pre-service teachers with appropriate infrastructure for technology integration is important.

Practically, this research could provide guidance for decision makers to improve the planning and design of policies regarding technology integration in pre-service teacher training programmes, especially in developing countries. For teacher educators, the findings can be used as a reference for technology-based teaching for PSTs. The model can benefit future studies addressing the predicting factors with regard to the integration of technology in education. For future research, the study could also be replicated for in-service teachers' technology integration.

Besides theoretical and practical implications, our study had some limitations. The study was limited to 457 PSTs in two Indonesian higher education institutions. For more instructional purposes, the number of institutions, population size, and a variety of majors could be improved. Other methods like observations and interviews could also be carried out to obtain an in-depth understanding of factors affecting technology integration into teaching for young teachers as well as the enablers and barriers. An experimental study could also be conducted to track pre-service teachers' technology integration before and after teaching practice.

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### Authors' Contributions

AH, RAR and FDY contributed to the writing of the article; AH, MM, AA, AM and AJ contributed reagents, materials, analysis tools or data and conducted the statistical analyses; all authors reviewed the final manuscript.

### Notes

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### References

- Adams LG 2011. Engaging middle school students with technology: Using real-time data to test predictions in aquatic ecosystems. *Science Scope*, 34(9):32–38.
- Ajzen I 1991. The theory of planned behavior. *Organizational Behavior and Human Decision Processes*, 50(2):179–211. [https://doi.org/10.1016/0749-5978\(91\)90020-T](https://doi.org/10.1016/0749-5978(91)90020-T)
- Aslan A & Zhu C 2017. Investigating variables predicting Turkish pre-service teachers' integration of ICT into teaching practices. *British Journal of Educational Technology*, 48(2):552–570. <https://doi.org/10.1111/bjet.12437>
- Bailey JM, Pomeroy JR, Shipp S, Shupla C, Slater SJ, Slater TF & Stork D 2011. Three methods of using online space data to support inquiry. *The Classroom Astronomer*, 2(3):20–23.
- Cheng EWL 2019. Choosing between the theory of planned behavior (TPB) and the technology acceptance model (TAM). *Educational Technology Research and Development*, 67(1):21–37. <https://doi.org/10.1007/s11423-018-9598-6>
- Cheng SL & Xie K 2018. The relations among teacher value beliefs, personal characteristics, and TPACK in intervention and non-intervention settings. *Teaching and Teacher Education*, 74:98–113. <https://doi.org/10.1016/j.tate.2018.04.014>
- Creswell JW 2014. *Research design: Qualitative, quantitative, and mixed methods approaches*. Thousand Oaks, CA: Sage.
- Ertmer PA 2005. Teacher pedagogical beliefs: The final frontier in our quest for technology integration? *Educational Technology Research and*

- Development*, 53(4):25–39.  
<https://doi.org/10.1007/BF02504683>
- Ertmer PA, Ottenbreit-Leftwich AT, Sadik O, Sendurur E & Sendurur P 2012. Teacher beliefs and technology integration practices: A critical relationship. *Computers & Education*, 59(2):423–435.  
<https://doi.org/10.1016/j.compedu.2012.02.001>
- Fatima JK, Ghandforoush P, Khan M & Di Mascio R 2019. Mobile learning adoption for tourism education in a developing country. *Current Issues in Tourism*, 22(4):420–427.  
<https://doi.org/10.1080/13683500.2018.1434135>
- Fishbein M & Ajzen I 1975. *Belief, attitude, intention and behaviour: An introduction to theory and research*. Reading, MA: Addison-Wesley.
- Graham CR, Borup J & Smith NB 2012. Using TPACK as a framework to understand teacher candidates' technology integration decisions. *Journal of Computer Assisted Learning*, 28(6):530–546.  
<https://doi.org/10.1111/j.1365-2729.2011.00472.x>
- Habibi A, Razak RA, Yusop FD, Mukminin A & Yaqin LN 2020. Factors affecting ICT integration during teaching practices: A multiple case study of three Indonesian universities. *Qualitative Report*, 25(5):1127–1144.
- Habibi A, Yusop FD & Razak RA 2020a. The dataset for validation of factors affecting pre-service teachers' use of ICT during teaching practices: Indonesian context. *Data in Brief*, 28:104875.  
<https://doi.org/10.1016/j.dib.2019.104875>
- Habibi A, Yusop FD & Razak RA 2020b. The role of TPACK in affecting pre-service language teachers' ICT integration during teaching practices: Indonesian context. *Education and Information Technologies*, 25:1929–1949.  
<https://doi.org/10.1007/s10639-019-10040-2>
- Hair JF, Jr, Black WC, Babin BJ & Anderson RJ 2010. *Multivariate data analysis* (7th ed). Upper Saddle River, NJ: Prentice Hall.
- Hair JF, Risher JJ, Sarstedt M & Ringle CM 2019. When to use and how to report the results of PLS-SEM. *European Business Review*, 31(1):2–24.  
<https://doi.org/10.1108/EBR-11-2018-0203>
- Hart SA & Laher S 2015. Perceived usefulness and culture as predictors of teachers attitudes towards educational technology in South Africa [Special issue]. *South African Journal of Education*, 35(4):Art. # 1180, 13 pages.  
<https://doi.org/10.15700/saje.v35n4a1180>
- Joo YJ, Park S & Lim E 2018. Factors influencing preservice teachers' intention to use technology: TPACK, teacher self-efficacy, and Technology Acceptance Model. *Educational Technology & Society*, 21(3):48–59.
- Koh JHL, Chai CS & Tsai CC 2010. Examining technological pedagogical content knowledge of Singapore pre-service teachers with a large-scale survey. *Journal of Computer Assisted Learning*, 26(6):563–573. <https://doi.org/10.1111/j.1365-2729.2010.00372.x>
- Kolodziejczyk I 2015. Mixed methods for study of gender issues in access, application, and attitudes toward ICT in higher education institutions in Papua New Guinea. *Sage Open*, 5(2):1–15.  
<https://doi.org/10.1177/2158244015581017>
- Kreijns K, Van Acker F, Vermeulen M & Van Buuren H 2013. What stimulates teachers to integrate ICT in their pedagogical practices? The use of digital learning materials in education. *Computers in Human Behavior*, 29(1):217–225.  
<https://doi.org/10.1016/j.chb.2012.08.008>
- Kriek J & Stols G 2010. Teachers' beliefs and their intention to use interactive simulations in their classrooms. *South African Journal of Education*, 30(3):439–456.  
<https://doi.org/10.15700/saje.v30n3a284>
- Lung-Guang N 2019. Decision-making determinants of students participating in MOOCs: Merging the theory of planned behavior and self-regulated learning model. *Computers & Education*, 134:50–62. <https://doi.org/10.1016/j.compedu.2019.02.004>
- Lynn MR 1986. Determination and quantification of content validity. *Nursing Research*, 35(6):382–385.  
<https://doi.org/10.1097/00006199-198611000-00017>
- Mei B, Brown GTL & Teo T 2018. Toward an understanding of preservice English as a foreign language teachers' acceptance of computer-assisted language learning 2.0 in the People's Republic of China. *Journal of Educational Computing Research*, 56(1):74–104.  
<https://doi.org/10.1177/0735633117700144>
- Mishra P & Koehler MJ 2006. Technological Pedagogical Content Knowledge: A framework for teacher knowledge. *Teachers College Record*, 108(6):1017–1054.
- Mohammadi H 2015. Investigating users' perspectives on e-learning: An integration of TAM and IS success model. *Computers in Human Behavior*, 45:359–374.  
<https://doi.org/10.1016/j.chb.2014.07.044>
- Price CA & Lee HS 2013. Changes in participants' scientific attitudes and epistemological beliefs during an astronomical citizen science project. *Journal of Research in Science Teaching*, 50(7):773–801. <https://doi.org/10.1002/tea.21090>
- Roschelle J, Abrahamson L & Penuel W 2004. *Integrating classroom network technology and learning theory to improve classroom science learning: A literature synthesis*. Paper presented at the annual meeting of the American Educational Research Association, San Diego, CA, 12–16 April.
- Sadaf A, Newby TJ & Ertmer PA 2012. Exploring pre-service teachers' beliefs about using Web 2.0 technologies in K-12 classroom. *Computers & Education*, 59(3):937–945.  
<https://doi.org/10.1016/j.compedu.2012.04.001>
- Salleh S 2016. Examining the influence of teachers' beliefs towards technology integration in classroom. *International Journal of Information and Learning Technology*, 33(1):17–35.  
<https://doi.org/10.1108/IJILT-10-2015-0032>
- Sánchez-Prieto JC, Huang F, Olmos-Migueláñez S, García-Peñalvo FJ & Teo T 2019. Exploring the unknown: The effect of resistance to change and attachment on mobile adoption among secondary pre-service teachers. *British Journal of Educational Technology*, 50(5):2433–2449.  
<https://doi.org/10.1111/bjet.12822>
- Sang G, Valcke M, Van Braak J & Tondeur J 2010.

- Student teachers' thinking processes and ICT integration: Predictors of prospective teaching behaviors with educational technology. *Computers & Education*, 54(1):103–112.  
<https://doi.org/10.1016/j.compedu.2009.07.010>
- Shmueli G, Ray S, Estrada JMV & Chatla SB 2016. The elephant in the room: Predictive performance of PLS models. *Journal of Business Research*, 69(10):4552–4564.  
<https://doi.org/10.1016/j.jbusres.2016.03.049>
- Taimalu M & Luik P 2019. The impact of beliefs and knowledge on the integration of technology among teacher educators: A path analysis. *Teaching and Teacher Education*, 79:101–110.  
<https://doi.org/10.1016/j.tate.2018.12.012>
- Teo T & Lee CB 2010. Explaining the intention to use technology among student teachers: An application of the Theory of Planned Behavior (TPB). *Campus-Wide Information Systems*, 27(2):60–67.  
<https://doi.org/10.1108/10650741011033035>
- Teo T, Sang G, Mei B & Hoi CKW 2019. Investigating pre-service teachers' acceptance of Web 2.0 technologies in their future teaching: A Chinese perspective. *Interactive Learning Environments*, 27(4):530–546.  
<https://doi.org/10.1080/10494820.2018.1489290>
- Teo T & Van Schaik P 2012. Understanding the intention to use technology by preservice teachers: An empirical test of competing theoretical models. *International Journal of Human-Computer Interaction*, 28(3):178–188.  
<https://doi.org/10.1080/10447318.2011.581892>
- Wang F, Kinzie MB, McGuire P & Pan E 2010. Applying technology to inquiry-based learning in early childhood education. *Early Childhood Education Journal*, 37(5):381–389.  
<https://doi.org/10.1007/s10643-009-0364-6>