The role of TPACK in affecting pre-service language teachers' ICT integration during teaching practices: Indonesian context



Akhmad Habibi¹ · Farrah Dina Yusop² · Rafiza Abdul Razak²

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Abstract

This study examined Indonesian pre-service language teachers' use of information and communication technology (UICT) during teaching practices. We used technological pedagogical and content knowledge (TPACK) framework to predict the UICT. The objective of the study is to determine if the TPACK is a valid model to explain Indonesian pre-service language teachers' UICT during teaching practices. 287 pre-service language teachers from three Indonesian universities completed a 38-item survey instruments based on the TPACK and UICT. The development of the survey instruments was done mainly through content validity index (CVI) and exploratory factor analysis (EFA). Findings of the study that were obtained through partial least squares structural equation modeling (PLS-SEM) informed 13 hypotheses. Overall, the TPACK components are interconnected and also reported to be a valid model to help explain Indonesian pre-service language teachers' UICT during teaching practices.

Keywords TPACK · Pre-service language teachers · UICT · Teaching practices

1 Introduction

Research on educational technology conducted in different contexts and settings have produced a common consensus that technology integration in education is a complex process (Mishra and Koehler 2006). One of many theoretical frameworks elaborated in educational technology research is TPACK that emerges as a framework combining

Akhmad Habibi akhmad.habibi@unja.ac.id

¹ University of Malaya/ LPDP Indonesia, Kuala Lumpur, Malaysia

² University of Malaya, Kuala Lumpur, Malaysia

fundamental dynamics of instructional activities using technology (Archambault and Barnett 2010). TPACK has recently been applied in either technology-based teaching activities or evaluation of teachers' technology integration (Agyei and Voogt 2012; Chai et al. 2012; Özgün-Koca et al. 2010; Valtonen et al. 2019). Although some research instruments on TPACK have been developed and examined for their interconnection (e.g. Archambault and Barnett 2010; Koh et al. 2010; Mumcu and Usluel 2010; Schmidt et al. 2009) that applied in various settings, a close investigation of the relationship between TPACK and UICT is still limited (Aslan and Zhu 2017; Reyes et al. 2017). As we were working on this study, the importance of interaction between some TPACK components and technology integration was also reported namely between pedagogical knowledge (PK) and ICT integration (Aslan and Zhu 2017), TPACK and intention to use Web 2.0 (Teo et al. 2018), and PK, technological knowledge (TK) and technology integration (Taimalu and Luik 2019).

However, those studies only summarized certain TPACK components' influences towards technology integration in education. Therefore, this study aimed at elaborating all TPACK components' interconnection and their roles in predicting UICT from the perspective of pre-service language teachers. To achieve the goals of the study, we first discussed the development and validation of research instruments designed specifically to measure teachers' technology integration knowledge and experiences as described in the TPACK framework and UICT.

2 Literature review

2.1 TPACK

The origin of TPACK was actually based on Shulman's pedagogical content knowledge (PCK) concept (Mishra and Koehler 2006). PCK is basically about the development of the most suitable teaching practices as well as the components. In the discussion about PCK, Shulman (1986) addressed a contrast idea of teaching content with general pedagogical approaches as well as teaching with content-specific pedagogy. The discussion on this was based on the historical development of teaching that argued content and pedagogy were included as "one indistinguishable body of understanding" (p.6). Regarding these meaningful principles of PCK, TPACK was introduced as a framework describing the components of effective integration of technology in instructional activities (Mishra and Koehler 2006; Schmidt et al. 2009). The appropriate way for technology integration within this framework needs teachers to possess a conceptualization formed by considering the interactions among the components; technology, content, and pedagogy" (Angeli and Valanides 2009). Although technology, content, and pedagogy are likely becoming a representation of different knowledge bases, interactions and link among the core concepts comprise the basic essence of the whole framework (Archambault and Barnett 2010). TPACK consists of seven knowledge bases, three of which are core knowledge bases; TK, PK, and content knowledge (CK). Meanwhile, other four components are established from the interactions among the core bases comprising technological content knowledge (TCK), PCK, technological pedagogical knowledge (TPK), and TPACK. The area, definition, and example of the seven TPACK components can be seen in Table 1.

TPACK area	Definition	Example
TK	Knowledge of how to use different technologies	Knowledge of how to use ICT
PK	Knowledge of different teaching and learning approaches and theories of learning	Knowledge of how to use inquiry-based learning method
CK	Knowledge of subject matter	Knowledge of language teaching
PCK	Knowledge of how to combine the CK and PK in order to make the content understandable	Knowledge of analogies to teach English as a foreign language
TCK	Knowledge of how to utilize appropriate technology to support teaching and learning approaches without considering the subject matter	Knowledge of <i>Kahoot</i> -application in teaching language
ТРК	Knowledge of how ICT is used by content experts	Knowing how to use content-specific simulations, CALL
TPACK	Knowledge of how to combine different areas and how to use appropriate pedagogical approaches for certain content with appropriate ICT	Knowledge of how to use the application for supportingstudents' brainstorming and sharing of ideas in language learning

Table 1 TPACK area, definition, and example (Valtonen et al. 2019)

2.2 Technology integration in language teaching

In nowadays' classrooms, the existence of technologies in educational settings has become a usual thing and a norm for many schools around the world (Castro 2012). In fact, according to Niemelä et al. (2016), digital tools such as tablets, computers, tablets, digital projection systems, digital cameras, and Internet have been considered among compulsory facilities not only for higher education institutions but also K-12 schools. Many K-12 schools are now in the race to use 1:1 technology program to ensure students and teachers have access to ICT (Keane and Keane 2019). This situation causes an expectation of cultural change in society in which technology-integrated teaching is consider fostering better learning for students (Prasojo et al. 2019). In fact, ability to integrate technologies into teaching has been listed as one of the requirements of recruiting new teachers including language teachers.

Specific technology integration is important in language teaching. Habibi et al. (2018) and Kabilan et al. (2010) reported that social media can help students practice their language meaningfully. Computer-based communication tools can improve students' language skills by facilitating interaction between students and native English-speakers (Golonka et al. 2014). Students have visual and auditory sources of learning language (Bernhardt 2010). Augmented reality was reported to help language learners coordinate and engage in the virtual world during problem solving tasks (Liu et al. 2016). In addition, Chen (2018) reported factors affecting the use of mobile learning among English learners. Regarding TPACK, language teachers enhanced second language (L2) interaction in form of TPACK by drawing students' attention for grammar through animation, supporting vocabulary use with image-based exercises and assessing the use of sentence patterns with a Chatbot (Tseng 2018). However, the use of more

general technology like ICT for L2 teaching is also suggested to investigate including from the perspectives of pre-service language teachers (Arrosagaray et al. 2019). In terms of TPACK, Mei et al. (2018) reported that pre-service teachers' knowledge of technology in a teacher education program is positively related to the use of technology in the classroom. While Tai (2015) informed that TPACK-in-Action workshops positively impacted on the 24 language teachers' teaching performance. In addition, Bustamante's (2019) qualitative study on Spanish teaching indicated positive learning experiences for technology, pedagogy, and content within technology integration.

2.3 The study and hypotheses

Adopting technology in teaching requires knowledge of technology, pedagogy, and content. TPACK can play a very important role in language teaching within the integration of ICT. Many studies have addressed the relationship among all TPACK components. In addition, some studies explored some TPACK components in relation to technology integration. However, a comprehensive TPACK interconnection and their influences towards technology integration have not much informed. Therefore, this study aimed at elaborating the interconnection and relationship with technology integration from the perspective of pre-service language teachers in teaching English. To achieve the aims of the study, 13 hypotheses were formulated (Fig. 1) that involve 8 variables; TK, CK, PK, TCK, PCK, TPK, TPACK, and UICT.



Fig. 1 Initial structural model

TK in this study is defined as knowledge of how to use different technologies perceived by Indonesian pre-service language teachers. TK has been proposed to have significant correlation with TCK and TPK (Chai et al. 2012; Dong et al. 2015; Pamuk et al. 2015; Scherer et al. 2017). Chai et al. (2012) failed to identify the relationship between TK and PCK or TPK. Meanwhile, Dong et al. (2015) reported that TK has significantly affected TCK (β =0.630; p<0.01) and TPK (β =0.460; p<0.01). Similarly, Pamuk et al. 2015 informed strong relationships between PK and TCK (β =0.740; p<0.01) as well as PK and TPK (β =0.620; p<0.01). Another report by Scherer et al. (2017) informed the influence of TK to TCK (β =0.860; p<0.01) and TK to TPK (β =0.810; p<0.01). Due to the roles of TK in predicting TCK and TPK, two hypotheses were proposed in this study;

H1: TK will positively and significantly predict TPK. H2: TK will positively and significantly predict TCK.

CK in this study is knowledge of subject matter that was also considered important in predicting two second-level knowledge bases, TCK and PCK (Chai et al. 2012; Dong et al. 2015; Pamuk et al. 2015). Even though Chai et al. (2012) found that CK was not a predictor for both TCK and PCK, Dong et al. (2015) reported that CK significantly affected TCK (β =0.130.; p<0.05). Meanwhile, Pamuk et al. (2015) revealed TCK (β =0.860; p<0.01) and PCK (β =.860; p<0.01) was statistically related to CK. 2 hypotheses were made regarding the role of CK;

H3: TK will positively and significantly predict TCK. H4: TK will positively and significantly predict PCK.

Similar to TK and CK, PK which is defined as knowledge of different teaching and learning approaches has been reported to significantly influence TPK and/or PCK (Chai et al. 2012; Dong et al. 2015; Pamuk et al. 2015; Valtonen et al. 2017). Chai et al. (2012) only reported the relationship between PK and TPK ($\beta = 0.520$; p < 0.01). Likewise, PK was also reported to be significant for TPK ($\beta = 0.280$; p < 0.01) in a study conducted by Pamuk et al. (2015). However, Dong et al. (2015) informed both TPK ($\beta = 0.350$; p < 0.01) and PCK ($\beta = 0.640$; p < 0.01) were significantly affected by PK.

H3: PK will positively and significantly predict TPK. H4: TK will positively and significantly predict PCK.

2.5 TPK, TCK, PCK, TPACK

TPK in this study is defined as knowledge of how ICT is used by content experts perceived by the respondents. Some previous studies have been addressing the interconnection between TPK and TPACK (Chai et al. 2012; Dong et al. 2015; Pamuk et al. 2015; Scherer et al. 2017). Pamuk et al. (2015) found and reported that TPK was correlated with TPACK (β =0.350; p<0.01). Scherer et al. (2017) also revealed that TPK strongly affect TPACK (β =0.980;

p < 0.01). On the other hand, Chai et al. (2012) and Dong et al. (2015) reported that TCK was not related to TPACK in their study findings. Regarding UICT, not many studies addressed TPK relationships with UICT. Graham (2011) quantitatively addressed that TPK has a great contribution to technology integration. To investigate comprehensively TPACK interconnection and their relationship with UICT, we addressed two hypotheses in regard to TPK;

H7: TPK will positively and significantly predict TPACK. H8: TPK will positively and significantly predict UICT.

TCK in this study refers to knowledge of how to utilize appropriate technology to support English teaching and learning approaches without the subject matter. Similar to TPK, not many TCK studies focused on the correlation between TCK and UICT. However, some researchers reported TCK as a strong predictor for TPACK (Chai et al. 2012; Dong et al. 2015; Pamuk et al. 2015). Pamuk et al. (2015) reported a strong correlation between TCK and TPACK (β =0.580; p<0.01) while Chai et al. (2012) found no relationship between TCK and TPACK. Similarly, Dong et al. (2015) reported that TCK positively predicted TPACK (β =0.490; p<0.01). Based on these backgrounds, we proposed 2 hypotheses regarding TCK as predictors of TPACK and UICT;

H9: TPK will positively and significantly predict TPACK. H10: TPK will positively and significantly predict UICT.

PCK is described as the knowledge of how to combine the CK and PK in order to make the content more understandable in English teaching. Some researchers have examined statistical correlation between PCK and TPACK (Chai et al. 2012; Dong et al. 2015; Pamuk et al. 2015; Scherer et al. 2017). Chai et al. (2012), Dong et al. 2015, and Pamuk et al. (2015) reported that no correlation emerged between PCK and TPACK. However, Scherer et al. (2017) informed that PCK was a strong predictor for TPACK (β = 0.980; *p* < 0.01). We proposed 2 hypotheses in relation to the role of PCK in predicting TPACK and UICT;

H11: TPK will positively and significantly predict TPACK.

H12: TPK will positively and significantly predict UICT.

TPACK in this study refers to knowledge of how to combine different areas and how to use appropriate pedagogical approaches for certain content with appropriate ICT. TPACK has been reported to fit predicting technology integration (Joo et al. 2018; Teo et al. 2018; Tondeur et al. 2017). Teo et al. (2018) informed TPACK's significance for intention to use Web 2.0 in China (β = 0.260; *p* < 0.01). Similarly Tondeur et al. (2017) also reported the positive relationship between TPACK and intention to use technology. However, TPACK was not significant predicting intention to use technology reported by Joo et al. (2018). To anticipate the relationship, a hypothesis was proposed for this study;

H13: TPACK will positively and significantly predict UICT.

3 Method

3.1 Conceptual model of the study

This study was conducted from October 2018 to July 2019 utilizing survey as the data collection method. Review of previous studies and the assessment of validity and reliability of the instruments were done before the data collection. The assessment of the model was conducted through partial least squares structural equation model (PLS-SEM). This study used a predictive approach to estimate the model for causality since the process of the study is not interfered by the assumption of data distribution (Hair et al. 2019).

3.2 Instrumentation

The review of literature helps a researcher define and analyse the theories and concepts of the theoretical framework of the research, as well as determine appropriate methods and instruments to be adapted in order to elaborate the research objectives (Hair et al. 2016). We adapted and constructed survey instruments from previous related studies; TPACK (Koh et al. 2010; Luik et al. 2018; Schmidt et al. 2009) and UICT (Aslan and Zhu 2017). As a result 44 items were generated in this stage. Afterward, the instruments were examined through face and content validity through discussion and content validity index (CVI) for social and cultural as well as setting differences (Lynn 1986).

For face validity, a panel of five users (three pre-service teachers, a program staff, and a teacher educator) was involved in discussing the adapted instruments. The process was done through interactive group discussion. For content validity, we discussed the instruments with five Indonesian experts. The experts were professors in the fields of educational technology and educational policy. After the discussion, some items were revised and 4 items were eliminated since they could not be used in the educational context of Indonesia resulting 40 items for further validation process.

We distributed the instruments to ten experts in educational technology and Indonesian educational policy. Twenty-seven experts were contacted; fifteen experts did not reply the call and 2 experts refused to participate. Each item of the survey instruments was evaluated by rating its relevance, clarity, and simplicity. The attributes of the items were rated on a 4-point scale (1 = not)relevant/ not clear/ not simple to 4 = very relevant/ very clear/ very simple (Halek et al. 2017; Lynn 1986). The experts' panel was requested to evaluate if the items covered all related aspects or if there were something missing in the components. The CVI was measured both at the item level (I-CVI) and scale level (S-CVI) for the three instruments' attributes. The I-CVI was measured by providing a score of 3 or 4 to the experts that were divided by the total number of experts. The score of 3 or 4 in the CVI theory represents positive responses (Lynn 1986). With a total of ten experts, the I-CVI should not be less than 0.780 (Polit and Beck 2009). In calculating the S-CVI (Polit and Beck 2009; Fleiss et al. 2004), the average portion of the items on one scale rated 3 or 4 (average agreement by experts = S-CVI/AVE) where the threshold value is 0.800 (Halek et al. 2017; Polit and Beck 2009). Most items' values were above the threshold values of 0.780 for I-CVI and 0.800 for S-CVI. However, PK4 was dropped because its I-CVI and S-CVI value was lower than the threshold. Additionally, a modified kappa (k^*) and the probability of chance occurrence (Pc) were also calculated.

Besides face and content validity, the instruments have also been examined through exploratory factor analysis (EFA) using some measurements; Sphericity Bartlett Test (p. <0.500), factor loading, Kaiser-Meyer-Olkin (> 0.800), Factor Loading \geq (0.500), Communalities (\geq 0.300), and Eigenvalue (\geq 1.00) which were proposed by Hair et al. (2010) and Pallant (2011). The survey instruments were piloted to 98 pre-service language teachers. 1 item (TPK4) was dropped due to its low loading value. Other items included in the EFA meet the measurements. Because PK4 and TPK4 were dropped, 38 indicators in eight constructs were included after the assessment of CVI and EFA (Table 2). The CVI and EFA data process can be accessed at Mendeley dataset repository.

3.3 Data collection

As face and content validity were done, we distributed the instruments to the respondents. The data were obtained from three Indonesian universities that have schools of education. To date, the letters of permission of the data collection were achieved and signed by each dean of the schools of education of each university. The distribution of the data was done using printed materials as it is recommended by the funder of this research. We spent a-three month time in collecting the data. All responses were compiled into Microsoft Excel and SPSS.

The population of this study is approximately 1.2 million student teachers in Indonesian PTTPs centered in 374 teacher training institutes or programs or PTTPs (Ministry of research, technology, and higher education, MoRTHE 2018). Meanwhile, the target population of this study covered all Indonesian pre-service language teachers. Through stratified sampling (Creswell 2014), we divided the target population from their universities. As a result, 310 instruments were distributed. However, only 287 data were measurable; University A (142), University B (67), and University C (78).

No	Construct	Indicators	No of items
1	ТК	TK1, TK2, TK3	3
2	PK	PK1, PK2, PK3, PK5, PK6, PK7	6
3	СК	CK1, CK2, CK3	3
4	TCK	TCK1, TCK2, TCK3	3
5	PCK	PCK1, PCK2, PCK3	3
6	TPK	TPK2, TPK3, TPK4	3
7	TPACK	TPACK1, TPACK2, TPACK3, TPACK4, TPACK5	5
8	UICT	UICT1, UICT2, UICT3, UICT4, UICT5, UICT6, UICT7, UICT8, UICT9, UICT10, UICT11, UICT12	12

Table 2 The indicators after CVI and EFA

The process of data conversion so that they can be processed by the computer was known as data preparation. The data preparation in this study was done to ensure the completeness and accuracy of the data as well as assurance that the data had no problems with outliers, missing values, non-normal distributions, and/or errors inputting the data (Hair et al. 2010). The assessment of skewness and kurtosis as well as Q-Q plot and histogram was carried out for the normality of the data.

3.5 Measurement models in the study

Measurement model was the examination process of the reliability and validity of the construct measures. Four reflective measurement models (reflective indicator loadings, internal consistency reliability, convergent validity, and discriminant validity) were examined in this process.

3.5.1 Reflective indicator loadings

We used PLS-SEM result format in reporting the reflective indicator. Table 3 informs the detail final results of all eleven constructs' reflective measurement model assessments. Details of the assessment and the results of reflective indicator show that some loadings were lower than the threshold or recommended values. From the result of the final PLS–SEM process, most indicators achieved the recommended value of ≥ 0.700 (Hair et al. 2019). However, few indicators show values below the threshold. All indicators having the value below 0.708 emerged from the construct of UICT namely UICT12 (0.653), UICT1 (0.656), UICT2 (0.674), UICT9 (0.690). The weak indicators were subsequently dropped from the process (Hair et al. 2016).

3.5.2 Internal consistency reliability

Internal consistency reliability was utilized for the evaluation of the consistency of results across items. In PLS-SEM method for this study, both Cronbach's alpha and composite reliability were tested (Hair et al. 2019). The values for internal consistency reliability are measured between 0 and 1, where the higher the value indicates a higher level of validity. The values of and Cronbach's alpha and composite reliability should be higher than 0.700 (Hair et al. 2019).

Table 3 performs the detail of Cronbach's alpha and composite reliability values. The Cronbach's alpha and the composite reliability values for most construct were stable, equivalent, and have good internal consistency reliability which exceeded the recommended value of 0.708 and were below the maximum value of 0.950. However, two constructs had values of greater than 0.950. PCK achieved 0.952 while TCK's value of composite reliability was 0.958. We deleted indicators (PCK3 and TCK3) that have semantically redundant items since the items measure very different aspects of the construct domain within a strong argument then the concerns of very high reliability are not assured (Hayduk and Littvay 2012).

3.5.3 Convergent validity

For the convergent validity, AVE values should be reported as suggested as the metric to measure (Hair et al. 2019). To calculate the AVE, we used PLS-SEM algorithm. The minimum acceptable AVE is 0.500 or higher, explaining 50% or more of the variance of the items for the construct. All constructs in this study had AVE values that are greater than 0.500 or explaining 50% or more about the variance of the items for the construct (Table 3).

	Outer loading	Cronbach's Alpha	Composite reliability	Average Variance Extracted (AVE)
 CK1	0.846	0.783	0.873	0.696
CK2	0.773			
CK3	0.879			
PCK1	0.951	0.859	0.933	0.875
PCK2	0.919			
PK1	0.719	0.844	0.885	0.563
PK2	0.741			
PK3	0.745			
PK5	0.775			
PK6	0.788			
PK7	0.730			
TCK1	0.955	0.870	0.938	0.884
TCK2	0.925			
TK1	0.834	0.758	0.861	0.676
TK2	0.897			
TK3	0.726			
TPACK1	0.788	0.798	0.868	0.623
TPACK2	0.822			
TPACK3	0.759			
TPACK5	0.787			
TPK2	0.844	0.751	0.858	0.668
TPK3	0.794			
TPK4	0.814			
UICT10	0.760	0.878	0.905	0.578
UICT11	0.698			
UICT5	0.772			
UICT6	0.788			
UICT7	0.782			
UICT8	0.815			
UICT9	0.698			

Table 3 Outer loading, Cronbach's alpha, composite reliability, and AVE

3.5.4 Discriminant validity

Discriminant validity is "the extent to which a construct is empirically distinct from other constructs in the structural model (Hair et al. 2019, p.13). When using the Fornell-Larcker criterion (traditional metric), "the shared variance for all model constructs should not be larger than their AVEs" (Fornell & Larcker, 1981 as cited in Hair et al. 2019, p. 14). It can be seen that the AVE of every construct in this study is higher than its shared variance (Table 4). From the criterion of Fornell-Larcker, it can be concluded that the discriminant validity for the quantitative data of this study was established.

Discriminant validity can be established when an indicator loading on a construct is higher than that of all of its cross-loadings on the other constructs (Hair et al. 2016). Table 5 exhibits all indicators' outer loadings as well as their cross-loadings for other indicators. It can be seen that the outer loadings (in bold and italic) for every construct was higher than the entire cross-loadings on the other constructs, for instance, the indicator CK1 has the highest loading value (0.846) compared to its cross loading on the other constructs (e.g. PCK = 0.375, PK = 0.531, and TCK = 0.333). Based on the finding of cross-loading assessment, it can be summarized that the discriminant validity was established through the assessment of outer loadings.

Discriminant validity issues emerge when the values of HTMT (the main consideration for the discriminant validity) are higher than the threshold. The threshold values for HTMT in this study (< 0.90) due to the reason that the constructs were conceptually similar; "an HTMT value above 0.90 suggests a lack of discriminant validity" (Hair et al. 2016, p. 141). Shown in Table 6, all values are below 0.90. The results indicate that all HTMT values were significantly different from 1 which is, therefore, establishing discriminant validity of the active constructs. After this process, 30 indicators were included for the assessment of the structural model.

4 Findings

The assessment of the structural model involved the examination of themodel's predictive capabilities. There were six systematic approaches (Hair et al. 2016). As elaborated earlier, the examination process involved in this study was begun with the

	CK_	PCK	PK	TCK	TK	TPACK	TPK	UICT
CK_	0.834							
PCK	0.412	0.935						
PK	0.540	0.539	0.750					
TCK	0.372	0.330	0.360	0.940				
TK	0.428	0.316	0.370	0.488	0.822			
TPACK	0.482	0.421	0.542	0.509	0.457	0.789		
TPK	0.380	0.370	0.452	0.515	0.474	0.696	0.817	
UICT	0.398	0.407	0.415	0.407	0.424	0.581	0.525	0.760

Table 4 Fornell-Larcker criterion

	CK_	PCK	РК	TCK	TK	TPACK	TPK	UICT
CK1	0.846	0.375	0.531	0.333	0.339	0.390	0.250	0.296
CK2	0.773	0.278	0.328	0.222	0.318	0.335	0.297	0.284
CK3	0.879	0.365	0.463	0.355	0.408	0.468	0.403	0.406
PCK1	0.404	0.951	0.559	0.338	0.306	0.446	0.372	0.419
PCK2	0.363	0.919	0.436	0.273	0.284	0.330	0.314	0.334
PK1	0.444	0.416	0.719	0.273	0.358	0.380	0.328	0.269
PK2	0.439	0.381	0.741	0.247	0.297	0.429	0.346	0.310
PK3	0.476	0.410	0.745	0.181	0.260	0.405	0.332	0.346
PK5	0.361	0.452	0.775	0.290	0.205	0.420	0.381	0.309
PK6	0.299	0.411	0.788	0.283	0.278	0.395	0.324	0.272
PK7	0.418	0.343	0.730	0.352	0.277	0.409	0.316	0.370
TCK1	0.394	0.333	0.363	0.955	0.500	0.528	0.526	0.429
TCK2	0.295	0.282	0.308	0.925	0.407	0.417	0.433	0.325
TK1	0.378	0.335	0.348	0.410	0.834	0.448	0.449	0.410
TK2	0.371	0.252	0.321	0.426	0.897	0.396	0.427	0.359
TK3	0.299	0.176	0.229	0.364	0.726	0.261	0.270	0.259
TPACK1	0.389	0.380	0.561	0.399	0.341	0.788	0.516	0.516
TPACK2	0.351	0.353	0.422	0.395	0.379	0.822	0.578	0.493
TPACK3	0.407	0.279	0.357	0.328	0.384	0.759	0.547	0.382
TPACK5	0.380	0.313	0.361	0.480	0.344	0.787	0.559	0.433
TPK2	0.332	0.350	0.431	0.459	0.378	0.551	0.844	0.428
ТРКЗ	0.360	0.290	0.229	0.439	0.478	0.552	0.794	0.413
TPK4	0.244	0.267	0.440	0.368	0.313	0.603	0.814	0.446
UICT10	0.220	0.306	0.264	0.368	0.359	0.481	0.429	0.760
UICT11	0.316	0.302	0.229	0.341	0.327	0.409	0.341	0.730
UICT5	0.374	0.313	0.357	0.265	0.312	0.473	0.416	0.772
UICT6	0.323	0.306	0.356	0.323	0.394	0.485	0.462	0.788
UICT7	0.289	0.327	0.338	0.303	0.274	0.442	0.380	0.782
UICT8	0.306	0.311	0.326	0.323	0.306	0.441	0.426	0.815
UICT9	0.294	0.308	0.343	0.234	0.267	0.337	0.320	0.702

Table 5 (Cross-loadings
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examination of collinearity, stage 1. The path coefficients (β) were then examined in stage 2. Further, In stage 3, the coefficient of determination (R^2) was examined. In stage 4, the effect size of f^2 was reported to assess the relevance of the construct in explaining selected endogenous constructs. In line with the f^2 effect size for the values of R^2 , we also calculated the Q^2 and its effect size in stage 5 and 6 (Hair et al. 2019).

4.1 Collinearity issue

Specifically, the sets of predictors were assessed for collinearity: (1) PCK, TCK, TPK, and TPACK as predictors of UICT; (2) PCK, TCK, and TPK as predictors of TPACK;

Table C UTMT

	CK_	PCK	РК	TCK	TK	TPACK	TPK	UICT
CK_								
PCK	0.493							
PK	0.651	0.621						
TCK	0.432	0.374	0.418					
TK	0.549	0.383	0.458	0.594				
TPACK	0.605	0.498	0.657	0.601	0.578			
TPK	0.496	0.456	0.561	0.631	0.62	0.899		
UICT	0.476	0.465	0.485	0.457	0.509	0.686	0.642	

(3) PK and TK as predictors of TPK; (4) CK and TK as predictors of TCK; and CK and PK as predictors of PCK (Table 7). All VIF values are below the threshold of three (<3) which suggested by Hair et al. (2019). Therefore, collinearity is not an issue for the model of this study.

4.2 Structural model relationship

To assess whether the relationships in the current study are significant between independent variables and dependent variables, we did the bootstrapping samples of 5000. Assuming a 5% significance level, all relationships informed in the structural model are significant, except the relationship between TCK and UICT. In terms of interconnection between core bases of knowledge (PK, CK, and TK) and the second-level bases of knowledge (TPK, TCK, and PCK), the PLS-SEM results inform the significances on all proposed relationships that support H1, H2, H3, H4, H5, and H6. In detail, TK is reported to have significant effects on TPK (β = 0.286; *p* < 0.01) and TCK (β = 0.321; *p* < 0.01). In addition, CK significantly predicts TCK (β = 0.281; *p* < 0.01) and PCK (β = 0.224; *p* < 0.01). The last core base, PK, is informed to be significant in determining TPK (β = 0.377; *p* < 0.01) and PCK (β = 0.447; *p* < 0.01). For these three

	СК	PCK	РК	TCK	TK	TPACK	TPK	UICT
СК		1.741		1.306			i i	
PCK						1.335		1.429
РК		1.741					1.263	
TCK						1.575		1.625
TK				1.306			1.263	
TPACK								2.366
TPK						1.528		2.258
UICT								

Table 7 Inner VIF value	s
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core base knowledge, the strongest relationship emerges between PK and PCK. In affecting TPACK, the second-level bases of knowledge (TPK, TCK, and PCK) are reported to be significant. Therefore, the three hypotheses (H7, H9, and H11) are statistically supported. TPACK is most strongly predicted by TPK ($\beta = 0.555$; p < 0.01) which is also the strongest correlation of all proposed hypotheses in this study. The weakest predictor affecting TPACK is TCK ($\beta = 0.144$; p < 0.01). Additionally, TPK is also significant predicting TPACK ($\beta = 0.199$; p < 0.01).

Besides the interconnection among TPACK components, this study is also proposed to investigate the role of 4 TPACK's component in predicting Indonesian pre-service language teachers' UICT. Through the bootstrapping process in PLS-SEM, 3 of the predictors are reported to statically predict UICT while one of them, TCK is not significant predicting UICT ((β =0.060; p > 0.05). The strongest variable predicting UICT is TPACK (β =0.354; p < 0.01) followed by TPK (β =0.153; p < 0.01). The weakest significant correlation emerges between PCK and UICT (β =0.092; p < 0.01). The results of the analysis support H10, H11, and H13; however, H8 is rejected. The complete exhibition of the bootstrapping results can be seen in Fig. 2 and Table 8.





Hypotheses	Path	Path coefficient (β)	p value	Significance
H1	TK -> TCK	0.321	<i>p</i> < .01	Yes
H2	TK -> TPK	0.286	<i>p</i> < .01	Yes
H3	CK ->TCK	0.281	<i>p</i> < .01	Yes
H4	CK -> PCK	0.224	<i>p</i> < .01	Yes
Н5	PK ->TPK	0.377	<i>p</i> < .01	Yes
H6	PK ->PCK	0.447	<i>p</i> < .01	Yes
H7	TCK -> TPACK	0.144	<i>p</i> < .01	Yes
H8	TCK ->UICT	0.060	0.065	No
Н9	TPK -> TPACK	0.555	<i>p</i> < .01	Yes
H10	TPK ->UICT	0.153	<i>p</i> < .01	Yes
H11	PCK -> TPACK	0.199	<i>p</i> < .01	Yes
H12	PCK ->UICT	0.092	<i>p</i> < .01	Yes
H13	TPACK ->UICT	0.354	p < .01	Yes

 Table 8
 Bootstrapping results

4.3 Level of *R*²

Coefficient of determination (R^2) is the value which measures the model's predictive accuracy and is calculated as the squares correlation between a specific endogenous construct's, or dependent variable's, actual and predicted values (Hair et al. 2016). R^2 value ranges between 0 and 1, where a higher value indicates a higher level of predictive accuracy. R^2 value of 0.75 is considered substantial, while 0.50 is moderate, and 0.25 is weak (Hair et al. 2016). Table 9 exhibits the result of R^2 ; PCK (0.381, weak), TCK (0.262, weak), TPACK (0.577, moderate), TPK (0.322, weak), UICT (0.322, weak). It can be considered that the data of this study is in a good level of predictive accuracy.

5 f^2 effect size

The effect sizes, denoted as f^2 , measures the impact of a predictor construct on an endogenous construct. f^2 assesses the change in the values of R^2 when a certain exogenous construct, is removed from the model. This is to measure the real impact

	R^2	Consideration
PCK	0.381	Weak
TCK	0.269	Weak
TPACK	0.577	Moderate
ТРК	0.322	Weak
UICT	0.322	Weak

Table 9 R ² Val	ue
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of an exogenous construct to the endogenous construct. The value of 0.02 is considered a small effect, 0.15 (medium effect), and 0.35 (large effect) (Hair et al. 2016). All exogenous constructs or predictors have effect sizes to endogenous constructs except for PCK -> UICT, TCK -> UICT, and TPK -> UICT (Table 10).

5.1 Assessing predictive relevance, Q^2

The last stage of this study model data presentation was done involving the predictive relevance of the model through the Stone-Geisser's Q^2 value. When the model shows predictive relevance, it is accurate to predict the data points of indicators in the model (Hair et al. 2016). In the structural model, Q^2 value which is larger than 0 for the reflective construct has an indication that the model's predictive relevance for the construct is achieved (0.02 as small; 0.15 as medium 0.35 as large). The procedure to obtain the Q^2 was done through blindfolding procedure using SmartPLS 3.0. (Hair et al. 2019). Results for the predictive relevance are reported in Table 11. From the table, it can be seen that all Q^2 values were above 0. The results of Q^2 facilitate support for the model's predictive relevance for all five endogenous constructs.

6 Discussion

The main goal of this study was to investigate interactions among TPACK components and examine their roles in predicting UICT from the perspectives of Indonesian preservice language teachers. Firstly, we developed research instruments measuring TPACK and UICT through face and content validity (CVI), reliability (Cronbach's alpha) and factor analysis (EFA). While developing and validating the instruments, recommendations of previous studies for TPACK (Koh et al. 2010; Luik et al. 2018; Schmidt et al. 2009) and for UICT (Aslan and Zhu 2017) in the literature were considered. For this

	Original f^2	Effect size Small	
CK -> PCK	0.047		
CK ->TCK	0.083	Small	
PCK -> TPACK	0.070	Small	
PCK ->UICT	0.009	No effect	
PK ->PCK	0.185	Medium	
PK - > TPK	0.166	Medium	
TCK -> TPACK	0.031	Small	
TCK ->UICT	0.003	No effect	
TK -> TCK	0.108	Small	
TK -> TPK	0.096	Small	
TPACK ->UICT	0.078	Small	
TPK -> TPACK	0.477	Large	
TPK ->UICT	0.015	No effect	

Table 10 f² effect size

	Q^2	Predictive relevance
СК	_	_
PCK	0.321	Medium
РК	_	_
TCK	0.227	Medium
TK	_	_
TPACK	0.345	Medium
ТРК	0.213	Medium
UICT	0.178	Medium

Table 11	Results	of	predictive	relevance.
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study, thirty-eight indicators are valid and reliable after EFA process; TPACK (26 indicators) and UICT (12 indicators). After the data preparation process, we measured the model by examining the model reflective indicator loadings, internal consistency reliability, convergent validity, and discriminant validity (Hair et al. 2019). From this process, 8 indicators were dropped since they did not meet the threshold values. As a result, 30 indicators were included for the assessment of the structural model.

From the assessment process, TPACK was strongly predicted by TPK while PK was the main predictor of TPK. Similarly, PK also predicts PCK with the strongest coefficient. Meanwhile, TCK is mostly predicted by TK. There are some correlations that are similar to previous studies; however, some of them are different. For instance, Pamuk et al. (2015) found the different result on the factor affect TPACK with TCK as the strongest predictor of TPACK. In addition, they reported PK strongly predicted TPK. Similar to this study, TK was informed as the strongest predictor for TCK and PK for PCK. In contrast, Chai et al. (2012) informed that TPACK was not predicted by TPK, TCK, and PCK; however, PK and CK were found to be related to TPACK. Luik et al. (2018) published an article coding other constructs' term for the TPACK components; technology, pedagogy, and content in which they were reported to have a significant relationship among all constructs.

A very few studies informed the relationship between TPACK complete paths and technology integration. Therefore, we filled the gap by examining TPACK interconnection and their roles predicting UICT. In determining UICT during teaching practices, TPACK is reported to be the strongest predictor followed by TPK and PCK. However, TCK is confirmed to have no correlation with UICT. This finding is similar to the findings of Teo et al. (2018), Tondeur et al. 2017) and Joo et al. (2018) that mention TPACK as a significant predictor for intention to use technology in education. Likewise, Aslan and Zhu (2017) informed the significant relationship between PK and UICT during teaching practices. However, Joo et al. (2018) reported that TPACK was not related to intention to use technology.

7 Conclusion

The central elaboration of this study has been obtained to elaborate the roles of TPACK in UICT during Indonesian pre-service language teachers' teaching practices. Before

identifying the TPACK roles on UICT, the investigation among TPACK components' interconnection was done which aims to comprehensively examine TPACK's roles affecting UICT so that the bias could be minimized for the proposed model (Vinzi et al. 2010).

Based on the data analysis, we suppose even though current TPACK format represents, at least schematically, validated relationships among knowledge bases perceived from pre-service language teachers in Indonesia and indicates that they all achieved similar impact on the development of TPACK, findings of this study suggest that relationships among TPACK components are complex involving 9 hypotheses e. Regarding its roles on UICT during teaching practices, the model has also been statistically valid and reliable informing that TPACK as a component is the strongest predictor followed by TPK and PCK.

Some implications and limitations are informed in this study. A better comprehension of pre-service language teacher's perceptions on TPACK can help to increase the efficiency of the programs regarding technology integration during teaching practices. A key goal of teacher education programs should aim to help pre-service teachers develop their perception about the needs of the new educational system regarding the integration of technology into teaching. In addition, the results of the current study should be considered for some methodological limitations. First, quantitative approach is not the only method for this kind of study. Studies through qualitative strategy are recommended for further informing the relationships that facilitates in-depth understanding of the situation. Although the proposed model elaborated the direct effects among the variables, intervention study to investigate indirect effects is suggested in order to discover more relationships among involve variables. Lastly, the findings and the proposed model are valid and reliable for Indonesian education and language teachers' context. Therefore, future studies are suggested to compare regarding countries and majors in different contexts.

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Data availability The dataset can be accessed at Mendeley dataset repository https://data.mendeley. com/datasets/s6brgxxktt/4

Compliance with ethical standards

Competing interests The author declares that there are no competing interests.

References

- Agyei, D. D., & Voogt, J. (2012). Developing technological pedagogical content knowledge in pre-service mathematics teachers through collaborative design. *Australasian Journal of Educational Technology*, 28(4), 547–564. https://doi.org/10.14742/ajet.827.
- Angeli, C., & Valanides, N. (2009). Epistemological and methodological issues for the conceptualization, development, and assessment of ICT–TPCK: Advances in technological pedagogical content knowledge (TPCK). *Computers & Education*, 52(1), 154–168. https://doi.org/10.1016/j.compedu.2008.07.006.
- Archambault, L. M., & Barnett, J. H. (2010). Revisiting technological pedagogical content knowledge: Exploring the TPACK framework. *Computers & Education*, 55(4), 1656–1662. https://doi.org/10.1016 /je.compedu.2010.07.009.

- Arrosagaray, M., González-Peiteado, M., Pino-Juste, M., & Rodríguez-López, B. (2019). A comparative study of Spanish adult students' attitudes to ICT in classroom, blended and distance language learning modes. *Computers & Education*, 134, 31–40. https://doi.org/10.1016/j.compedu.2019.01.016.
- 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.
- Bernhardt, E. B. (2010). Teaching other languages. Educational Practices Series, 20, 1-29.
- Bustamante, C. (2019). TPACK and teachers of Spanish: Development of a theory-based joint display in a mixed methods research case study. *Journal of Mixed Methods Research*, 13(2), 163–178. https://doi. org/10.1177/15586898177121199.
- Castro, R. (2012). Blended learning in higher education: Trends and capabilities. *Education and Information Technologies*, 24(4), 1–24. https://doi.org/10.1007/s10639-019-09886-3.
- Chai, C. S., Koh, J. H. L., Ho, J. H. N., & Tsai, C. C. (2012). Examining preservice teachers' perceived knowledge of TPACK and Cyberwellness through structural equation Modelling. *Australasian Journal of Educational Technology*, 28(6), 1000–1019. https://doi.org/10.14742/ajet.807.
- Chen, C. P. (2018). Understanding mobile English-learning gaming adopters in the self-learning market: The uses and gratification expectancy model. *Computers & Education*, 126, 217–230. https://doi.org/10.1016 /j.sbspro.2016.07.055.
- Creswell, J. W. (2014). A concise introduction to mixed methods research. Sage Publications.
- Dong, Y., Chai, C. S., Sang, G. Y., Koh, J. H. L., & Tsai, C. C. (2015). Exploring the profiles and interplays of pre-service and in-service teachers' technological pedagogical content knowledge (TPACK) in China. *Journal of Educational Technology & Society*, 18(1), 158–169.
- Fleiss, J. L., Levin, B., & Paik, M. C. (2004). The measurement of interrater agreement. In W. Shewart & S. Wilks (Eds.), *Statistical methods for rates and proportions* (pp. 598–626). John Hoboken: Wiley & Sons.
- Fornell, C., & Larcker, D. F. (1981). Structural equation models with unobservable variables and measurement error: Algebra and statistics. *Journal of Marketing Research*, 18(3), 382–388. https://doi.org/10.1177 /002224378101800313
- Golonka, E. M., Bowles, A. R., Frank, V. M., Richardson, D. L., & Freynik, S. (2014). Technologies for foreign language learning: A review of technology types and their effectiveness. *Computer Assisted Language Learning*, 27(1), 70–105. https://doi.org/10.1080/09588221.2012.700315.
- Graham, C. R. (2011). Theoretical considerations for understanding technological pedagogical content knowledge (TPACK). *Computers & Education*, 57(3), 1953–1960. https://doi.org/10.1016/j. compedu.2011.04.010.
- Habibi, A., Mukminin, A., Riyanto, Y., Prasojo, L. D., Sulistiyo, U., Sofwan, M., & Saudagar, F. (2018). Building an online community: Student teachers' perceptions on the advantages of using social networking services in a teacher education program. *Turkish Online Journal of Distance Education*, 19(1), 46–61.
- Hair, J. F., Anderson, R. E., Babin, B. J., & Black, W. C. (2010). Multivariate data analysis: A global perspective (7th ed.). New Jersey: Pearson Prentice Hall.
- Hair, J. F., Hult, G. T. M., Ringle, C., & Sarstedt, M. (2016). A primer on partial least squaress structural equation modeling (PLS-SEM). London: Sage publications.
- Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (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.
- Halek, M., Holle, D., & Bartholomeyczik, S. (2017). Development and evaluation of the content validity, practicability and feasibility of the innovative dementia-oriented assessment system for challenging behaviour in residents with dementia. *BMC Health Services Research*, 17(1), 554 https://www.ncbi. nlm.nih.gov/pubmed/28806934.
- Hayduk, L. A., & Littvay, L. (2012). Should researchers use single indicators, best indicators, or multiple indicators in structural equation models? *BMC Medical Research Methodology*, 12(1), 159. https://doi. org/10.1186/1471-2288-12-159.
- Joo, Y. J., Park, S., & Lim, E. (2018). Factors influencing preservice teachers' intention to use technology: TPACK, teacher self-efficacy, and technology acceptance model. *Journal of Educational Technology & Society*, 21(3), 48–59.
- Kabilan, M. K., Ahmad, N., & Abidin, M. J. Z. (2010). Facebook: An online environment for learning of English in institutions of higher education? *The Internet and Higher Education*, 13(4), 179–187. https://doi.org/10.1016/j.iheduc.2010.07.003.
- Keane, T., & Keane, W. (2019). A vision of the digital future-government funding as a catalyst for 1 to 1 computing in schools. *Education and Information Technologies*, 1–17. https://doi.org/10.1007/s10639-019-09988-y.

- Koh, J. H. L., Chai, C. S., & Tsai, C. C. (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.
- Liu, Y., Holden, D., & Zheng, D. (2016). Analyzing students' language learning experience in an augmented reality mobile game: An exploration of an emergent learning environment. *Proceedia-Social and Behavioral Sciences*, 228, 369–374. https://doi.org/10.1016/j.compedu.2018.06.016.
- Luik, P., Taimalu, M., & Suviste, R. (2018). Perceptions of technological, pedagogical and content knowledge (TPACK) among pre-service teachers in Estonia. *Education and Information Technologies*, 23(2), 741– 755. https://doi.org/10.1007/s10639-017-9633-y.
- Lynn, M. R. (1986). Determination and quantification of content validity. Nursing Research, 35(6), 382-385.
- Mei, B., Brown, G. T., & 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, M. J. (2006). Technological pedagogical content knowledge: A framework for teacher knowledge. *Teachers College Record*, 108(6), 1017–1054. https://doi.org/10.1111/j.1467-9620.2006.00684.x.
- (2018). *Grafik* [Active student graphic based on majors]. Retrieved from https://forlap.ristekdikti.go. id/mahasiswa/homegraphbidang.
- Mumcu, F. K., & Usluel, Y. K. (2010). A scale development study of integration of ICT into learning and teaching process according to TPACK. In A. Isman (Ed.), *International educational technology conference 2010* (pp. 1419–1423). Turkey: Istanbul.
- Niemelä, P., Isomöttönen, V., & Lipponen, L. (2016). Successful design of learning solutions being situation aware. *Education and Information Technologies*, 21(1), 105–122. https://doi.org/10.1007/s10639-014-9311-2.
- Özgün-Koca, S. A., Meagher, M., & Edwards, M. T. (2010). Preservice teachers' emerging TPACK in a technology-rich methods class. *The Mathematics Educator*, 19(2), 10–20.
- Pallant, J. (2011). Survival manual. A step by step guide to data analysis using SPSS. 4th edition, Crows Nest, NSW: Allen & Unwin.
- Pamuk, S., Ergun, M., Cakir, R., Yilmaz, H. B., & Ayas, C. (2015). Exploring relationships among TPACK components and development of the TPACK instrument. *Education and Information Technologies*, 20(2), 241–263. https://doi.org/10.1007/s10639-013-9278-4.
- Polit, D. F., & Beck, C. T. (2009). Essentials of nursing research: Appraising evidence for nursing practice. Philadelphia: Lippincott Williams & Wilkins.
- Prasojo, L. D., Habibi, A., Yaakob, M. F. M., Mukminin, A., Haswindy, S., & Sofwan, M. (2019). An explanatory sequential study on Indonesian principals' perceptions on ICT integration barriers. *Electronic Journal of e-Learning*, 17(1), 1–10.
- Reyes Jr., V. C., Reading, C., Doyle, H., & Gregory, S. (2017). Integrating ICT into teacher education programs from a TPACK perspective: Exploring perceptions of university lecturers. *Computers & Education*, 115, 1–19. https://doi.org/10.1016/j.compedu.2017.07.009.
- Scherer, R., Tondeur, J., & Siddiq, F. (2017). On the quest for validity: Testing the factor structure and measurement invariance of the technology-dimensions in the technological, pedagogical, and content knowledge (TPACK) model. *Computers & Education*, 112, 1–17. https://doi.org/10.1016/j. compedu.2017.04.012.
- Schmidt, D. A., Baran, E., Thompson, A. D., Mishra, P., Koehler, M. J., & Shin, T. S. (2009). Technological pedagogical content knowledge (TPACK) the development and validation of an assessment instrument for preservice teachers. *Journal of Research on Technology in Education*, 42(2), 123–149. https://doi. org/10.1080/15391523.2009.10782544.
- Shulman, L. S. (1986). Those who understand: Knowledge growth in teaching. *Educational Researcher*, 15(2), 4–14. https://doi.org/10.3102/0013189X015002004.
- Tai, S. J. D. (2015). From TPACK-in-action workshops to classrooms: CALL competency developed and integrated. *Language Learning & Technology*, 19(1), 139–164.
- 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., Sang, G., Mei, B., & Hoi, C. K. W. (2018). 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.

- Tondeur, J., Pareja Roblin, N., van Braak, J., Voogt, J., & Prestridge, S. (2017). Preparing beginning teachers for technology integration in education: Ready for take-off? *Technology, Pedagogy and Education, 26*(2),
- 157–177. https://doi.org/10.1080/1475939X.2016.11935566.
 Tseng, J. J. (2018). Exploring TPACK-SLA interface: Insights from the computer-enhanced classroom. Computer Assisted Language Learning, 31(4), 390–412. https://doi.org/10.1080 /09588221.2017.1412324.
- Valtonen, T., Sointu, E., Kukkonen, J., Kontkanen, S., Lambert, M. C., & Mäkitalo-Siegl, K. (2017). TPACK updated to measure pre-service teachers' twenty-first century skills. *Australasian Journal of Educational Technology*, 33(3).
- Valtonen, T., Sointu, E., Kukkonen, J., Mäkitalo, K., Hoang, N., Häkkinen, P., Järvelä, S., Näykki, P., Virtanen, A., Pöntinen, S., Kostiainen, E., & Tondeur, J. (2019). Examining pre-service teachers' technological pedagogical content knowledge as evolving knowledge domains: A longitudinal approach. *Journal of Computer Assisted Learning*, 1–12. https://doi.org/10.1111/jcal.12353.
- Vinzi, V. E., Trinchera, L., & Amato, S. (2010). PLS path modeling: From foundations to recent developments and open issues for model assessment and improvement. In *Handbook of partial least squares* (pp. 47– 82). Springer, Berlin, Heidelberg.

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