

AI Use during Teaching Practice: Pre-service English as a Foreign Language Teachers' Perspectives

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Abstract—Artificial Intelligence (AI) is rapidly advancing in education, making it vital to understand how pre-service teachers embrace AI tools, especially in resource-constrained English as a Foreign Language (EFL) contexts like Indonesia, where empirical studies on technology integration are still limited. This study examined the relationships between beliefs, knowledge, and the use of AI during teaching practice among Indonesian Pre-Service English as a Foreign Language Teachers (PSEFLT). The Theory of Planned Behavior (TPB) was extended by the Technological Pedagogical and Content Knowledge (TPACK) framework. TPB consists of several variables, namely Subjective Norms (SN), Attitudes (AT), Perceived Behavioral Control (PBC), Intention to Use AI (IUAI), and Use of AI (UAI), which are the main components of the TPB extended by TPACK and Technological Pedagogical Knowledge (TPK). A survey instrument was adapted and validated using face and content validity, a content validity index, and a measurement model. The study employed Partial Least Squares Structural Equation Modeling (PLS-SEM) to analyze the primary data ($n = 773$). We confirmed most hypotheses with satisfactory path coefficients, t-values, and p-values. PBC was the most significant factor affecting IUAI. UAI was primarily predicted by IUAI. Belief factors excelled knowledge factors in affecting IUAI and UAI. PSEFLT are suggested to broaden their beliefs and knowledge to personalize learning and improve EFL instruction, and for teacher education programs to increase the program's effectiveness and efficiency.

Keywords—artificial intelligence, English as a foreign language, pre-service teachers, Theory of Planned Behavior (TPB), Technological Pedagogical and Content Knowledge (TPACK)

I. INTRODUCTION

Artificial Intelligence (AI) technology has become integral to various fields, including education. AI in education offers a wide range of potential to improve learning and teaching [1, 2]. For example, AI can help personalize learning, analyze student data to identify individual needs, and provide educational resources efficiently and effectively [3–5]. For English as a Foreign Language (EFL) teachers who are still in the pre-service stage, beliefs and knowledge about the use of AI in teaching practice are

essential aspects [6, 7]. The two factors predicted teachers' use of technology in education [8]. AI can provide many benefits; however, teachers may hesitate to use it in teaching without understanding how to use it effectively [9].

Notably, this study explored how Pre-Service English as a Foreign Language Teachers (PSEFLT) perceive AI in education, which is essential to provide deeper insight into the factors influencing behavioral intention and use [7, 10]. By understanding these perspectives, policymakers can develop more effective training and professional development strategies for the use of AI in education. Recommendations for developing curriculum and teacher training programs for AI use in education can benefit technological developments and future educational needs. Therefore, the current research aims to examine PSEFLT's beliefs and knowledge regarding the use of AI during teaching practice. The Theory of Planned Behavior (TPB) for belief includes five factors: Subjective Norms (SN), Attitudes (AT), Perceived Behavioral Control (PBC), Intention to Use AI (IUAI), and Use of AI (UAI). Meanwhile, Technological Pedagogical Knowledge (TPK) and Technological Pedagogical and Content Knowledge (TPACK) represent knowledge in this study.

II. LITERATURE REVIEW

Technology use challenges are rapidly changing as new systems and tools, such as AI, are continually being used in education. In this study, AI use is defined as teaching plans, activities, and assessments with the use of AI during teaching practice. AI can assist aspiring teachers in English as a Foreign Language (EFL) by providing adaptive learning through platforms such as Knewton and DreamBox, which tailor materials to individual students' needs. Virtual assistants and chatbots, such as EdTech Chatbot, can answer student questions in real time and assist with routine tasks, allowing aspiring teachers to focus on more complex aspects of teaching. Tools like Gradescope enable rapid and accurate automated grading, while apps like Duolingo and Rosetta Stone help improve students' language skills by providing customized practice and specific feedback.

Additionally, AI can design teaching materials tailored to the class's needs and develop simulations and educational games to increase student motivation and engagement. Pre-service teachers' views toward the use of technology in the classroom are multifaceted and evolving. They possess the skills and abilities to utilize technology [11]. However, they have a limited understanding and ideas about using technology in the classroom [12]. Pre-service teachers may encounter challenges when using technology to meet specific curriculum needs and operate an efficient classroom. The condition is particularly true now, as educational institutions regularly introduce sophisticated, new technologies to the market. Effective technology integration requires specific knowledge and values, as well as technology for information gathering, communication, and entertainment. Prior research has reported the importance of pre-service teachers acquiring the necessary attitudes and skills to effectively utilize technology in their teaching practicums [8, 13].

Current literature typically overlooks the theoretical distinction between standard technology integration (e.g., learning management system, multimedia) and AI-specific adoption. Unlike general technologies, AI systems are generative, adaptive, and autonomous, raising issues in explainability, ethical decision-making, data protection, and dynamic pedagogical adaptation. AI use, critical evaluation, bias mitigation, and teacher agency are not fully captured by standard technology integration frameworks. Pre-service teachers must develop these skills. Thus, this study views AI use in education as involving higher-order cognitive and ethical demands that distinguish it from earlier ICT integration studies and require a more complex theoretical treatment.

A. The Study

Some models have been informed by assessments of AI use in educational contexts to help educators better integrate AI into teaching. Furthermore, specific combination models for AI use assessment in education have also been documented [14–17]. For example, the Unified Technology Acceptance and Use of Technology (UTAUT) and TPB were modified to assess the variables influencing students' intention to experience virtual reality [14]. In another study in China, AI use was investigated by integrating TPB and the technology acceptance model [15]. The current study proposed a deeper understanding of PSEFLT's beliefs and knowledge affecting IUAI and UAI to provide a stronger theoretical and instructional framework.

TPB (beliefs) and TPACK (knowledge) form a strong complementary framework compared to TAM, UTAUT, or standalone TPACK models. TAM and UTAUT emphasize perceived utility and ease of use but underemphasize social norms, actual behavioral control, and domain-specific pedagogical-content knowledge, which pre-service teachers in practicum contexts value. However, pure TPACK experiments generally ignore motivation and volition. This model measures teachers' psychological readiness (SN, AT, PBC) and professional capacity to successfully integrate AI by extending TPB with TPACK. This hybrid approach covers "will" and "skill," explaining AI uptake in teaching practice better than single-theory approaches.

B. TPB

First presented was the TPB, a theoretical framework for understanding people's views about things, objects, or methods of doing things [14]. According to the TPB, beliefs influence behavioral intentions. Thus, intentions impact behavior [14]. Indirect measures of willingness or intent are represented by three types of key opinions or beliefs (SN, AT, and PBC). To date, the TPB has been extensively used to gauge people's perceptions to elucidate their intent to engage in a particular activity in the context of artificial intelligence [7, 16, 18–24].

SN in this study refers to PSEFLT's perception of social pressure to perform or not perform a particular behavior; belief about whether significant people of the participants, who were Indonesian preservice EFL teachers (such as parents, friends, and peers), consider that they should engage in AI use during teaching practicum. SN has been an essential factor affecting IUAI and AIU in education [16, 21, 25]. For instance, the TPB framework was extended to examine the perceptions of 796 Nigerian pre-service teachers regarding the use of AI in learning, revealing that Subjective Norms (SN) were a significant factor influencing behavioral intention [21]. Similarly, another study reported that a substantial relationship emerged between SN and the IUAI in medical education [25]. However, IUAI in learning was not significantly affected by SN perceived by Chinese students [16].

AT refers to the Indonesian PSEFLT's positive or negative evaluation of performing the behavior within the context of this study. It encompasses the individual's perception of the behavior's results and their assessment. If PSEFLT believe that using AI will lead to positive outcomes, they are likely to have a favorable AT towards AI integration [24, 26]. Another study examined the correlation between biology teachers' AT towards AI and behavioral intention to tutor, with a path coefficient of 0.400 (significant) [12]. Another study also reported that AT ($\beta = 0.198$; $p < 0.001$) significantly predicted IUAI in learning among students in Saudi Arabia [26].

The PBC in this study investigates how PSEFLT perceive their ability to use AI for teaching during their tenure as trainee teachers at related schools. Some earlier research studies discussed the connections between PBC and behavioral intention and actual AI behavior in education [21–23, 27, 28]. For instance, PBC has been identified as an important factor of behavioral intention [23]. Further, PBC was also found to significantly affect Malaysian academicians' behavioral intention to integrate AI into their teaching [22]. However, PBC was reported to have an insignificant correlation with the IUAI in Genetics teaching in Nigerian universities [24]. All TPB factors (SN, AT, and PBC) were listed to examine their relationship to IUAI, and two variables (PBC and IUAI) were listed as factors affecting UAI. Five hypotheses were noted for the model in this study:

H3: SN will be a significant predictor of IUAI.

H4: AT will have a significant effect on IUAI.

H5: PBC will strongly predict IUAI.

H8: PBC will significantly affect UAI.

H9: IUAI will positively and significantly predict UAI.

C. TPACK

TPACK is a well-known model of teacher expertise that integrates technology, content, and pedagogy, and is an extension of Pedagogical Content Knowledge (PCK) [29]. Three primary components of the TPACK framework are technological knowledge, content knowledge, and pedagogical knowledge. TPACK, technological pedagogical knowledge, technological content knowledge, and pedagogical content knowledge are the four combined domains formed by the three primary components. To extend TPB, we included two factors (TPK and TPACK). We describe TPK as the use of technology to transform and improve teaching methods. TPACK is the intersection of all three knowledge areas, emphasizing the integration of these areas to enhance teaching and learning. The roles of TPK and TPACK in shaping the intention to use and the use of technology within a specific educational context have been documented in prior studies [30–33]. Though commonly used for general technology integration, TPACK has yet to be applied to AI-specific teaching. Current AI-TPACK investigations are shallow. TPACK is linked to Gen-AI adoption intentions among higher education faculty but not among pre-service instructors, using SEM-ANN [32]. Pre-service teachers are willing to integrate AI into STEM, yet view TPACK as a peripheral construct. TPK and TPACK affect pre-service EFL teachers' capacity to integrate AI tools with pedagogical techniques and English content knowledge during practicum [30, 33]. This gap explains why this work emphasizes TPK and TPACK as knowledge factors within an expanded TPB model.

Regarding the use of AI in education, a few TPACK-related studies have been reported [34–38]. By using a hybrid approach that combines SEM and artificial neural networks, the complex relationships between TPACK and the adoption of Gen-AI were informed [12]. The research uncovered a significant determinacy of TPACK on AI use, as perceived by 242 participants. Another study also reported a robust correlation between TPACK and virtual reality use among Indonesian pre-service teachers [35]. Few studies have examined the relationship between TPK, IUAI, and UAI; however, researchers on non-AI technology integration have found a vital role for TPK in behavioral intention and behavior [32, 33]. Therefore, four proposed hypotheses were included to examine the roles of TPK and TPACK in relation to IUAI and UAI (Fig. 1).

H1: TPK will be a significant predictor of IUAI.

H2: TPACK will have a robust role in affecting IUAI.

H6: TPK will have a significant association with UAI

H7: TPACK will be a significant predictor of UAI.

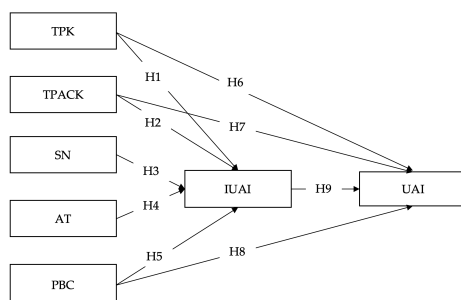


Fig. 1. The proposed model of the study encompasses nine hypotheses, involving seven variables.

III. MATERIALS AND METHODS

The current research employs a survey design as its method of investigation. The survey items were created and modified, marking the start of the instrumentation phase. These focus on seven domains: TPK, TPACK, SN, AT, PBC, IUAI, and UAI. We also incorporated demographic data alongside the primary survey results. The survey instruments were adapted from prior research on TPACK and TPK [30, 39, 40], and TPB [15, 41, 42]. The survey instrument for UAI during teaching practice was also modified from prior related research [43, 44]. The Likert scale was five points, with anchors ranging from 1 (strongly disagree) to 5 (strongly agree). The instrument was translated from English to Indonesian using a back-translation process. For that reason, three translation professionals were involved [45]. We compared the questionnaires using a face and content validation method to predict if the translation appropriately reflected the clarity of the statements for PSEFLT. Seven PSEFLT who shared the same traits as the primary responders also assessed the statements' simplicity and clarity, a part of face validity [46].

A. CVI and Pilot Study

Seven EFL and educational technology experts were consulted for the survey items. Eleven items were eliminated during the content validity process; other items were amended based on suggestions from experts regarding issues such as unclear language and statements. Furthermore, ten experts were given the instrument to predict the Content Validity Index (CVI). Every item was assessed for clarity, simplicity, and relevance. A 4-point rating system was used to rate the items: 1 was "not relevant, not simple, not clear," and 4 was "very relevant, very simple, very clear" [47, 48]. We asked the experts to assess the scale level (S-CVI-scoring from the average agreement by experts = S-CVI/AVE) and item level (I-CVI - scoring 3 or 4 divided by the number of experts). If ten experts are involved, the S-CVI should be higher than 800, and the I-CVI should be greater than 78. All I-CVI and S-CVI indicators ranged above 0.780, and a value of 0.800 satisfied the requirements.

Developing instruments that accurately represent the variables specified by the conceptual framework is a crucial step in conducting survey research. Among the procedures is a pilot study, an early evaluation strategy for items' development [49, 50]. Similar to the primary target respondents, PSEFLT who had completed or were in the process of completing their teaching practicum were also among the pilot study's respondents. The survey instrument was piloted with 100 respondents and examined for reliability using Cronbach's alpha. All values exceeded the threshold, making the instrument reliable for the main data collection.

B. Sampling

Based on statistics from Indonesian higher education, this study's population comprises more than 1.3 million pre-service teachers enrolled in more than 300 pre-service teacher training programs. Nevertheless, the target population of this study comprised Indonesian PSEFLT in one Indonesian province in Sumatra. Partial Least Squares Structural Equation Modeling (PLS-SEM) was used for the

statistical investigation. PLS-SEM models with numerous indicators and significant components, even with sample sizes as small as 10 [49]. That being said, the study's sample size, more than 1000, was rather substantial. Using stratified sampling, a total of 855 PSEFLT's were given the survey. Following data cleaning, 773 responses were quantified, yielding a response rate of 90.4%.

IV. RESULT AND DISCUSSION

PLS-SEM combined a measurement model with a structural model and computed the study's results. A measurement model evaluates a model's construct validity and reliability [51, 52]. In the measurement model steps, we computed the data to inform the loading values, consistency reliability, convergent validity, and discriminant validity. The loading value should be higher than 0.500 [8, 53]. The statistical analysis was conducted after assessing the normality of the data (Table 1). In SPSS, data normality was assessed by examining Skewness and Kurtosis, as shown in Table 2 [54]. Skewness and kurtosis values between -2 and +2 are considered acceptable evidence of normality [55]. For the measurement model's loadings, the PLS algorithm in SmartPLS reported that all items had loadings greater than 0.500, except for TPACK4, which was eliminated because its loading was below 0.50 (Fig. 2). TPACK4 ("I can provide leadership in helping other preservice EFL teachers coordinate content, AI technology, and teaching approaches at my school") was removed due to a low outer loading (<0.50). This item was distinct, focusing on leadership and mentoring rather than TPACK application. Its removal did not weaken the construct, as the four remaining items sufficiently cover the core TPACK dimensions: technology, pedagogy, and content integration. Keeping only items with strong loadings improved validity (AVE = 0.663) and consistency without losing content validity. Future studies could refine leadership items for pre-service groups. Reliability assessment in the current model is defined as the evaluation attempt for the consistency of computational values across items [56].

The reliability criteria used in this study comprise three assessments: Cronbach's alpha, Rho_A, and Composite Reliability (CR). Reliability values ranged between 0 and 1; the higher the value, the better the reliability. Cronbach's alpha, rho_A, and CR for sufficient reliability should be higher than 0.700 [56–58]. Table 2 presents the results of the computation in SmartPLS, meeting all three criteria with thresholds of 0.70 or higher. IUAI reported the lowest alpha value (0.785), while TPK reported the highest (0.933). Rho_A values were between 0.790 (IUAI) and 0.950 (TPK), while CR values were 0.874 (IUAI) to 0.947 (TPK). All values confirm that the data have appropriate reliability values.

Convergent validity, which is a component of construct validity, states that tests with comparable or identical constructs ought to have a high degree of correlation; Average Extracted Variance (AVE) is used to report convergent validity [59–61]. A variable's AVE should be at least 0.500, or 50% of the variance explained by the indicators. The AVE values for each factor were greater than 0.500 (AT = 0.616; IUAI = 0.699; PBC = 0.607; SN = 0.649; TPACK = 0.699; TPK = 0.881; UAI = 0.647). Additionally,

discriminant validity assesses whether constructs that ought not to be related are unrelated [60, 61]. The most robust discriminant validity assessment includes evaluating the Heterotrait-Monotrait (HTMT) ratio of correlations, with HTMT values typically less than 0.900 [51]. The values should be less than 900; all HTMT values are sufficiently calculated, ranging from 0.451 to 0.846 (Table 3). Consequently, there are no problems with discriminant validity in the current study's measurement model. The survey instrument used in this study was deemed valid and reliable based on evaluations of the measurement models (loadings, reliability, convergent and discriminant validity). Appendix A contains the final valid and reliable survey instrument (Tables A1–A7).

Table 1. Mean, SD, kurtosis, skewness, loading

Variable	Mean	SD	Kurtosis	Skewness	Load
AT1	3.959	0.721	-0.451	-0.181	0.810
AT2	3.899	0.759	-0.768	-0.057	0.757
AT3	4.019	0.741	-0.092	-0.337	0.834
AT4	4.022	0.700	-0.743	-0.103	0.836
AT5	3.825	0.715	-0.445	-0.046	0.739
AT6	3.908	0.730	0.118	-0.302	0.725
AT7	3.967	0.716	-0.515	-0.155	0.786
IUAI1	4.064	0.768	0.028	-0.494	0.859
IUAI2	3.823	0.796	0.216	-0.380	0.835
IUAI3	4.044	0.751	0.014	-0.425	0.814
PBC1	3.931	0.763	0.130	-0.330	0.734
PBC2	3.788	0.716	-0.425	-0.024	0.797
PBC3	3.783	0.769	-0.176	-0.118	0.810
PBC4	3.698	0.725	0.006	-0.014	0.803
PBC5	3.757	0.762	-0.006	-0.121	0.748
SN1	3.697	0.773	-0.238	-0.082	0.808
SN2	3.657	0.825	0.310	-0.279	0.820
SN3	3.794	0.811	-0.593	-0.091	0.821
SN4	3.622	0.778	-0.169	-0.005	0.800
SN5	3.941	0.792	-0.370	-0.278	0.779
TPACK1	3.655	0.685	-0.419	0.178	0.816
TPACK2	3.735	0.647	-0.314	0.043	0.820
TPACK3	3.703	0.688	-0.421	0.107	0.817
TPACK5	3.766	0.679	-0.429	0.064	0.804
TPK1	3.728	0.690	-0.571	0.190	0.949
TPK2	3.774	0.669	-0.397	0.050	0.925
TPK3	3.767	0.678	-0.466	0.086	0.943
UAI1	4.186	0.717	0.142	-0.563	0.782
UAI2	3.768	0.758	0.113	-0.269	0.760
UAI3	3.858	0.795	0.437	-0.466	0.865
UEA4	3.808	0.842	0.262	-0.458	0.806

Table 2. Reliability of the constructs

Variable	Alpha	rho_A	CR
AT	0.895	0.896	0.918
IUAI	0.785	0.790	0.874
PBC	0.837	0.839	0.885
SN	0.865	0.865	0.902
TPACK	0.831	0.831	0.887
TPK	0.933	0.950	0.947
UAI	0.817	0.819	0.880

A. Structural Model

By evaluating the intercorrelation among the variables in question, a structural model enables researchers to examine the relationships simultaneously. The current research used bootstrapping (5000 samples) to estimate the structural model. Bootstrapping is a suggested PLS-SEM approach for generating random sub-samples from the original data [51, 57]. Using the SmartPLS program, PLS-SEM is a nonparametric method for assessing the statistical significance of path coefficients (β), t values, and p-values. It is advised that the model fit indices be provided before the structural model. In PLS-SEM-based research, the

Standardized Root Mean Square Residual (SRMR) is recommended for assessing model fit (< 0.08). This technique also includes the geodesic distance (d_G) and the squared Euclidean distance (d_ULS) [62, 63]. The d_ULS and d_G are likewise satisfactory at 1.493 and 1.776, and the SRMR value satisfied the requirements at 0.055, which was less than 0.080 [62].

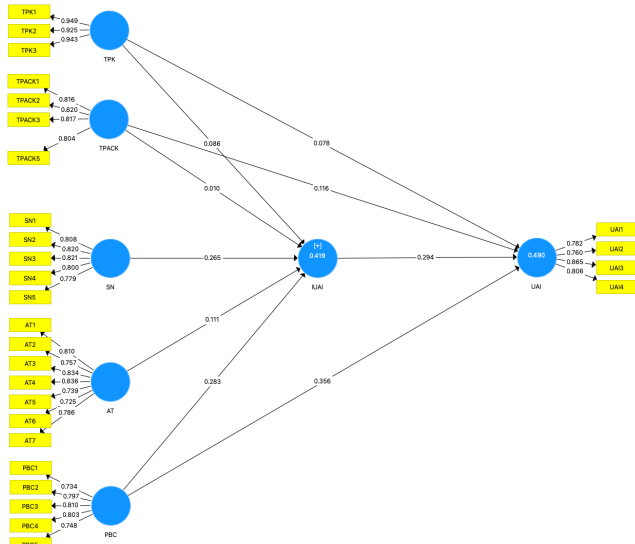


Fig. 2. The measurement model was calculated through SmartPLS, resulting in 31 reliable and valid items.

Table 3. HTMT

Variable	AT	IUAI	PBC	SN	TPACK	TPK	AVE
AT							0.616
IUAI	0.651						0.699
PBC	0.846	0.720					0.607
SN	0.782	0.695	0.799				0.649
TPACK	0.723	0.562	0.696	0.730			0.663
TPK	0.543	0.451	0.517	0.488	0.664		0.881
UAI	0.770	0.733	0.765	0.704	0.609	0.480	0.647

Table 4. Structural model of the study

H	Path	β	t value	p values	Sig.	f ²
H1	TPK $\rightarrow$ IUAI	0.086	2.368	0.018	Yes	0.007
H2	TPACK $\rightarrow$ IUAI	0.010	0.235	0.814	No	0.003
H3	SN $\rightarrow$ IUAI	0.265	5.604	0.000	Yes	0.048
H4	AT $\rightarrow$ IUAI	0.111	2.041	0.041	Yes	0.010
H5	PBC $\rightarrow$ IUAI	0.283	5.604	0.000	Yes	0.057
H6	TPK $\rightarrow$ UAI	0.078	2.086	0.037	Yes	0.011
H7	TPACK $\rightarrow$ UAI	0.116	2.526	0.012	Yes	0.008
H8	PBC $\rightarrow$ UAI	0.356	7.791	0.000	Yes	0.127
H9	IUAI $\rightarrow$ UAI	0.294	6.322	0.000	Yes	0.105

We employed the bootstrapping process in SmartPLS to assess the significance of the relationships. We reported the significance using β , t-value, and p-value, assuming a 5% significance level [52, 64, 65]. Table 4 and Fig. 3 show that most correlations found in the structural model are significant, except for one path coefficient between TPACK and IUAI. The PLS-SEM analysis demonstrates the importance of each hypothesis (H1, H3, H4, H5, H6, H7, H8, and H9). PBC was the largest predictor of IUAI ($\beta = 0.283$; $p < 0.01$; $t = 5.604$), followed by SN ($\beta = 0.265$; $p < 0.01$; $t = 5.604$); TPK ($\beta = 0.086$; $p < 0.05$; $t = 2.368$) and AT ($\beta = 0.111$; $p < 0.05$; $t = 2.041$) showed the smallest roles on IUAI. PBC also played the most significant role in predicting UAI, with a path coefficient of 0.356. Besides, the link between IUAI and UAI was also significantly strong ($\beta = 0.294$; $p < 0.01$; $t = 6.322$). The least reliable predictors

of UAI were TPK ($\beta = 0.078$; $p < 0.05$; $t = 2.086$) and TPACK ($\beta = 0.116$; $p < 0.05$; $t = 2.562$).

The f-square (f^2) effect size analysis shows the significant influence of each predictor in the PLS-SEM model. According to Cohen's guidelines (0.02 = small, 0.15 = medium, 0.35 = large), PBC has the strongest medium effect on UAI, with an f^2 value of 0.127, indicating that it substantially contributes to users' intention to adopt AI. A moderate effect from IUAI $\rightarrow$ UAI at $f^2 = 0.104$ indicates significant explanation. Unlike AT $\rightarrow$ UAI: 0.008, SN $\rightarrow$ UAI: 0.049, TPACK (0.008), TPK (0.011), and TPACK (0.000), most other pathways have minor predictive powers. The model shows that PBC and IUAI drive UAI variance, while attitudinal, normative, and technological knowledge factors contribute little.

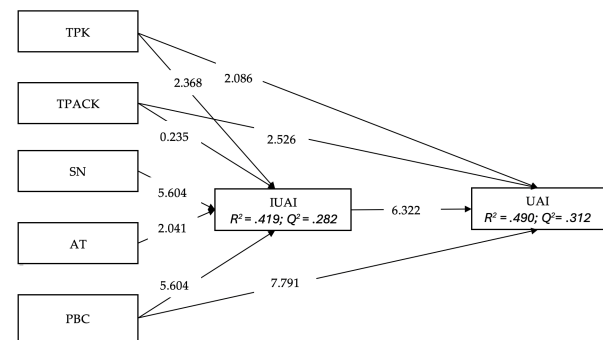


Fig. 3. The structural model includes eight confirmed hypotheses with the highest t-value of 7.791.

Following the significance test results, we used predictive relevance (Q^2) and coefficient of determination (R^2) as statistical measures in the PLS-SEM-based study. R^2 measures the model's prediction accuracy [51, 52, 65]. The range of R^2 values is 0 to 1, defined as considerable, moderate, and weak at values of 0.75, 0.50, and 0.25, respectively [51]. The R^2 results for IUAI (0.419, medium) and UAI (0.490, medium) are shown in Fig. 3. Similarly, Q^2 is a metric used to evaluate prediction performance [51, 52]. Statistical computations for the predictive relevance are presented using Q^2 values [65]. When it demonstrates predictive significance, the model accurately predicts the data points of its indicators. The SmartPLS process was conducted using blindfolding of participants. Values greater than 0 signify the attainment of the construct's Q^2 : 0.02 for small, 0.15 for medium, and 0.35 for considerable value. The model's predictive significance was enhanced by Q^2 values of 0.282 for IUAI and 0.312 for UAI.

B. Discussion

The results of the PLS-SEM show that PBC, which represents PSEFLT's opinions of their ability to use technology in their teaching, was the most robust predictor of IUA and UAI. Prior studies also revealed that PBC was a decisive factor affecting the IUAI and UAI [21–23, 27, 28]. For instance, PBC was found to play a significant role in IUAI among lecturers and students in higher education institutions [27], and PBC was also found to significantly affect Malaysian lecturers' intention to integrate AI into instruction [22]. However, PBC significantly affected IUAI's teaching of Genetics in Nigerian universities [24]. In predicting the UAI, another report confirmed the importance of PBC facilitation [28].

Another crucial component in predicting IUAJ was SN, representing PSEFLT's perspectives from their colleagues, professors, and families, who encourage the use of AI in teaching. The hypothesis suggests that cultural and social factors strongly predict IUAJ during the teaching practicum, explaining this result. Compared with non-Asian cultures, the results also demonstrate that SN is a significant predictor of intention to use AI [21]. Asians are more often acknowledged as a group and are held in high regard by others [22]. As a result, it should come as no surprise that their surroundings or social network significantly predicted the IUAJ of Indonesian PSEFLT's. The results corroborated earlier research indicating that SN is a highly significant predictor of AI intention [16, 21, 25].

The results also demonstrated a substantial relationship between AT and IUAJ. Previous findings on AI use in education also revealed that AT was strongly correlated with behavioral intention [24, 26]. Another research investigated the relationship between teachers' AT and behavioral intention to use AI, with a p -value of less than 0.001 (significant) [24]. Alzahrani in 2023 [26] also reported similar findings on AI use in Saudi Arabian education. The results show that the TPB factors (AT, SN, and PBC) are positively and substantially linked with IUAJ. As a result, fostering positive AT, SN, and PBC is critical to improve the intention to use AI among PSEFLT's. Based on the TPB paradigm, the results also demonstrated a substantial association between IUAJ and UAI. This result is consistent with the prevailing knowledge in behavioral psychology, which holds that intentions are frequently a positive predictor of future behavior.

TPK also significantly predicted IUAJ ($\beta = 0.086$) and UAI ($\beta = 0.037$). The results support previous research highlighting the importance of TPK in shaping both behavioral intention and actual behavior [32, 33]. From the TPACK factor, the finding informs that it does not play a salient role in determining IUAJ ($\beta = 0.010$); however, it has a robust correlation with UAI ($\beta = 0.116$). The results corroborate earlier research demonstrating the role of TPACK in predicting IUAJ and behavior [34–38]. The statistical reports of TPK and TPACK, representing knowledge, were lower than those of SN, AT, and PBC, which constituted belief factors in predicting intention and behavior to use AI in teaching practice. The results could be merged, since the PSEFLT's, as respondents in this study, have limited knowledge of integrating AI technology with pedagogy and content in their instructional activities. As a result, this study offers more evidence for beliefs than for knowledge regarding UAI. The study adds to the body of knowledge about the variables influencing AI in education, particularly during the teaching practicum. The differences in TPACK and TPB components must be acknowledged in teacher education to improve the usage of AI. The assets that teachers possess ought to be emphasized and utilized. Pre-service teachers who have a high degree of belief in and knowledge about the integration of AI in education should be motivated to strengthen their areas of weakness and build on their strengths.

V. CONCLUSION

This research uses PLS-SEM techniques and a structural

model to demonstrate the relationships between belief/knowledge factors and AI in teaching practice (intention and use). This study found that the links between beliefs (SN, AT, and PBC) and AI integration were more significant than those between knowledge (TPK and TPACK) and AI integration. To encourage the development of technological knowledge, pre-service teachers must believe in the benefits of AI technology. PSEFLT's can broaden their perspectives and knowledge to personalize learning and improve EFL instruction. These variables can also aid teacher education by increasing the program's effectiveness and efficiency. Further investigation into this result is necessary to better prepare new teachers for AI in their teaching practice. In teacher education, it may be beneficial to place greater emphasis on nurturing teachers' beliefs alongside the development of their professional knowledge. While both are essential, fostering positive beliefs can play a valuable role in shaping effective teaching practices and long-term professional growth from the perspectives of the current study. The results provide pre-service teachers with a deeper understanding of the gaps in their knowledge and beliefs, which could help inform the design of teacher education programs. When creating these kinds of programs, policymakers should consider which rules or regulations best govern AI in education regarding belief and knowledge. For example, policymakers could improve AI-based courses to further enhance learning by emphasizing the development of belief and knowledge about the advantages of technology for teaching. Enhancing pre-service teachers' use of AI in their instruction could also require special attention, addressing issues to bridge the gap between belief and knowledge. Such belief- and knowledge-based AI training could benefit their interactions, decision-making, and behavior as teachers, helping discover teaching strategies for efficient preparation and evaluation.

The current study revealed certain limitations. The methodology does not accurately assess the causal direction; instead, it merely acknowledges the existence of links and the strength of a causal hypothesis. Another drawback of the self-reported questionnaire may be its brevity; researchers could expand it to include more information about belief, knowledge, and educational AI, such as AI ethics and AI bias. For AI use in education, we recommend employing additional strategies, such as experimentation, interviewing, and observation, to enhance understanding of knowledge and beliefs. Additionally, contexts and settings could be modified to encompass a broader range of program components. The step would improve the quality of AI research by enriching future discoveries. Furthermore, integrating demographic data is essential for understanding variations in the parameters predicting AI integration in higher education. Finally, the larger and more representative sample sizes in the quantitative study may increase confidence in the generalizability of future research, especially since the current study's sample is limited to a single Indonesian province.

APPENDIX

Survey instrument [English version]

Demographic Information

1. University

2. Gender
 - a. Female
 - b. Male
3. Age range
 - a. 18–19
 - b. 20–21
 - c. >22
4. If you use AI technology like ChatGPT, Gemini, or other tools for your EFL teaching, please continue.
Please tick in the provided column.
1 = Very disagree
2 = Disagree
3 = Neutral
4 = Agree
5 = Very agree

Table A1. Technological pedagogical content

No	Statement	1	2	3	4	5
1.	I can choose AI technology that enhance my EFL teaching.					
2.	My teacher education program has caused me to think more deeply about how AI technology could influence my EFL teaching approaches I use in my classroom.					
3.	I am thinking critically about how to use AI technology in my EFL teaching.					
4.	I can adapt the use of the AI technology that I am learning about to different teaching activities.					

Table A2. Technological pedagogical and content knowledge (TPACK)

No	Statement	1	2	3	4	5
1.	I can teach EFL that combine my content area, AI technology, and teaching approaches appropriately.					
2.	I can select AI technology to use in my classroom that enhances what I teach, how I teach, and what EFL students learn.					
3.	I can use strategies that combine content, technology, and teaching approaches that I learned from my EFL course					
4.	I can choose AI technology that enhances the content and pedagogy in my EFL teaching.					

Table A3. Attitude

No	Statement	1	2	3	4	5
1.	I think that AI technology integration improves engagement with content and students					
2.	Integrating AI during my EFL teaching practice is relevant with the 21 st century teaching					
3.	I think that technology integration enriches the learning experience through innovative tools					
4.	I think that AI technology integration helps facilitate understanding of material/concepts					
5.	I feel that AI technology is easy to use					
6.	AI technology integration caters to the needs of different learning styles					
7.	I think that using AI technology improves students' evaluation in their learning					

Table A4. Subjective norms

No	Statement	1	2	3	4	5
1.	My colleagues expect me to use AI technology for my EFL teaching.					
2.	The principal of my school expects me to use AI technology for my EFL teaching.					
3.	My students assume that I can use AI technology for teaching.					
4.	Parents of my students expect me to use AI technology for my EFL teaching.					
5.	My EFL professor expects me to integrate					

AI technology into my EFL teaching.

Table A5. Perceived behavioral control

No	Statement	1	2	3	4	5
1.	I think that the advantages of using AI technology outweigh the disadvantages.					
2.	I have high self-efficacy in personal use in my EFL teaching using AI technology.					
3.	I think access to learning outside the classroom supports AI technology use.					
4.	I think that access to AI technology is not a problem in technology integration.					
5.	I think supporting human resources is not an issue for AI technology integration.					

Table A6. Behavioral intention

No	Statement	1	2	3	4	5
1.	I will use AI technology for EFL simulation like speaking practice and writing tasks.					
2.	I will use AI technology in my EFL teaching.					
3.	I will use AI technology to prepare material in my EFL teaching.					

Table A7. Behavior

No	Statement	1	2	3	4	5
1.	I use search engines (e.g., Google, Yahoo, etc.) to look for information on the Internet for teaching preparation.					
2.	Using AI technology, I create instructional materials (e.g., handouts, tests, etc.).					
3.	I create lesson plans using AI technology.					
4.	I use AI technology for my EFL teaching evaluation					

CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

BAW and AH conceptualized the study, designed the methodology, and supervised the project. CB, HAW, MSOF, TMA, IWS, and HA collected and analyzed the data. BAW and AH wrote the original draft. All authors reviewed, revised the manuscript, and approved the final version.

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