Factors affecting Indonesian pre-service EFL teachers' AI acceptance and use

Fatores que afetam a aceitação e o uso da IA por parte dos futuros professores de inglês como língua estrangeira da Indonésia

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Abstract

Integrating artificial intelligence in language education, particularly for pre-service English as a Foreign Language (EFL) teachers, presents unique challenges and opportunities. This research seeks to extend the technology acceptance model (TAM) by integrating technological pedagogical and content knowledge (TPACK) to predict behavioral intentions and actual use of AI technologies in an EFL context. Employing partial least squares structural equation modeling, the sample consisted of 436 pre-service EFL teachers. The findings showed that perceived ease of use impacts perceived usefulness (β=0.674) and attitudes (β=0.387). Perceived usefulness affects attitudes (β=0.452) and AI-behavioral intention (β=0.216). The attitudes variable influences AI-behavioral intention (β=0.206). Technological content and technological pedagogical knowledge contribute to TPACK (β=0.278, β=0.311). TPACK impacts AI-behavioral intention (β=0.350) and AI-use (β=0.557). By extending the TAM with TPACK, this study offers insights into optimizing AI adoption among future language educators, thereby fostering innovative teaching practices that enhance language learning experiences for students. The current study covers two areas of Sustainable Development Goals (SDGs): Higher education quality in the EFL area (SDG 4 - Quality Education) and digital transformation in education (SDG 17 – Partnerships for the Goals).

Keywords: Artificial Intelligence. Pre-service EFL teacher. Survey. TAM. TPACK.

Resumo

A integração da inteligência artificial no ensino de idiomas, particularmente para futuros professores de inglês como língua estrangeira (EFL), apresenta desafios e oportunidades únicos. Esta pesquisa busca estender o modelo de aceitação de tecnologia (TAM) integrando o conhecimento pedagógico tecnológico e o conhecimento de conteúdo (TPACK) para prever intenções comportamentais e o uso real de tecnologias de IA em um contexto de EFL. Empregando modelagem de equações estruturais de mínimos quadrados parciais, a amostra consistiu de 436 futuros professores de EFL. Os resultados mostraram que a facilidade de uso percebida impacta a utilidade percebida ($\beta = 0,674$) e as atitudes ($\beta = 0,387$). A utilidade percebida afeta as atitudes ($\beta = 0,452$) e a intenção comportamental da IA ($\beta = 0,216$). A variável atitudes influencia a intenção comportamental da IA ($\beta = 0,206$). O conteúdo tecnológico e o conhecimento pedagógico tecnológico contribuem para o TPACK ($\beta = 0,278$, $\beta = 0,311$). O TPACK impacta a intenção comportamental da IA ($\beta = 0,350$) e o uso da IA ($\beta = 0,557$). Ao estender o TAM com o TPACK, este estudo oferece *insights* sobre como otimizar a adoção da IA entre futuros educadores de línguas, promovendo práticas de ensino inovadoras que aprimoram as experiências de aprendizagem de línguas para os alunos. O estudo atual abrange duas áreas dos

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Objetivos de Desenvolvimento Sustentável (ODS): qualidade do ensino superior na área de inglês como língua estrangeira (ODS 4 - Educação de Qualidade) e transformação digital na educação (ODS 17 - Parcerias para os Objetivos).

Palavras-chave: Inteligência Artificial. Professor de inglês em formação inicial. Pesquisa. TAM. TPACK.

1 Introduction

Artificial intelligence (AI) in teaching English as a foreign language (EFL) stands out as a frontier and pivot for innovation when technology is constantly changing (Darwin *et al.*, 2024). Therefore, training pre-service EFL teachers to become familiar with AI technologies and their use to improve language acquisition becomes essential. Prior studies have explored AI use in education through frameworks such as UTAUT, IS Success model, TAM, and TPACK (Ma, 2024; Venkatesh, 2022; Yoon; Kim, 2023). The current research elaborates on how pre-service EFL teachers perceived AI in their teaching practicum. The broad applicability of traditional models like TAM, which combine perceived usefulness (PU), perceived ease of use (PEOU), and attitudes (ATT) to forecast AI-behavioral intention (AI-BI) and AI-use (AI-USE), is frequently criticized for lacking specific contextual nuances. A more specialized method of comprehending AI acceptance and use in the unique setting of language education is provided by this study's integration TAM with TPACK (technological pedagogical and content knowledge). TPACK highlights the interaction between knowledge of technology, pedagogy, and content. This study incorporates the TPACK framework, including technological pedagogical knowledge (TPK) and technological content knowledge (TCK), as the variables examined are grounded in technology-related knowledge domains.

The intersection of the proposed hypotheses is crucial because teaching languages includes developing linguistic information as well as cultural and communicative skills (Al-Adwan *et al.*, 2024). The current study may assist in establishing professional development programs that better reflect pre-service EFL teachers' needs. The programs could lead to more creative English teaching approaches and increased classroom technology adoption. To prepare students for 21st-century education, policymakers need to understand how future teachers will respond to advanced AI tools, like language learning apps and AI feedback systems. Given the phenomenon, this study elaborated on Indonesian pre-service EFL teachers' AI-BI and AI-USE during teaching practicum. Thus, this research sits at the intersection of acceptance, pedagogy, technology, and language instruction to contribute to the development of Indonesian higher education. To meet the objectives of the research, 11 hypotheses were proposed within this study context, detailed in the literature review section (Figure 1).

2 Literature review

Understanding how teachers use technology is vital in the fast-changing world of educational technology. The current study proposes a new paradigm that combines TAM with the TPACK frameworks to better comprehend AI acceptance and use for pre-service EFL teachers (Al-Adwan *et al.*, 2024; Habibi; Yaakob; Al-Adwan, 2023). Figure 1 shows how these two models are integrated in the suggested paradigm. PEOU, PU, and ATT are the main elements of the TAM, which was established to explain user acceptance. PEOU is the degree to which a person believes a system will be easy to use, whereas PU is the degree to which it will improve their work performance. Our model represents these two notions, which lead to attitudes towards using technology, pre-service EFL teachers' positive or negative feelings about using a particular technology (Davis; Bagozzi; Warshaw, 1989). TPACK framework organizes how teachers' technology, pedagogy, and content knowledge improve learning (Mishra; Koehler, 2009). The concept used in this study covers three factors, TCK, TPK, and TPACK, to influence AI acceptance and use in the EFL field. The model includes AI-BI, influenced by PU, ATT, TCK, TPK and TPACK components, underlining AI's importance in current education and AI-USE, which is expected to be influenced by AI-BI and TPACK. Prior studies have combined TAM and TPACK in their studies, reporting the significance of supporting variables to understand the use and acceptance of technology with TPACK during instructional activities, such as virtual reality in education (Thohir *et al.*, 2023), technology (Cheng *et al.*, 2024), and AI (Sun *et al.*, 2024).

2.1 Perceived ease of use (PEOU)

We emphasize the importance of creating AI tools that are not only strong in function but also user-friendly and accessible, particularly for pre-service EFL teachers (Davis; Bagozzi; Warshaw, 1989). In this study, PEOU is hypothesized to influence PU directly. Fundamental to TAM, the idea that PEOU influences PU has been extensively researched in several educational situations, including language teaching and learning and in a study with pre-service teachers, including those with an EFL concentration (Allali; Ghouati, 2025; Dehghani; Mashhadi, 2024; Liu; Ma, 2023; Ma, 2024; Wu; Wang; Wang, 2023; Zou et al., 2023). Wu, Wang, and Wang (2023) discovered that EFL learners were more inclined to view AI technologies as beneficial for learning when they were thought to be simple to use and navigate. In Iran (Dehghani; Mashhadi, 2024), it was revealed that EFL teachers' PEOU and PU were significantly correlated in the context of ChatGPT use in English teaching. PEOU influences ATT (positive or negative feelings about AI use in EFL teaching practicum) toward AI use in teaching practicum. Some prior studies have explored this relationship in technology adoption in education (Al-Abdullatif, 2023; Chen; Zou, 2024; Ma, 2024; Wu; Wang; Wang, 2023; Yuviler-Gavish; Halutz; Neta, 2024). Wu, Wang, and Wang (2023) through a mixed method study investigated the relationship between PEOU and ATT about AI in the setting of pre-service EFL learners. They observed that EFL learners' opinions toward AI tools improved when they perceived them as less intimidating and more uncomplicated to include in their learning tools. The observation is fundamental in language education, where language learning and teaching complexity may first make learners nervous about implementing new technology in learning (Wu; Wang; Wang, 2023). The findings might be promising, increasing the desire to learn and apply AI, creating an atmosphere that permits and promotes innovation in language teaching and learning. However, several studies disclosed the insignificant relationship between PEOU and ATT (Al-Abdullatif, 2023; Chen; Zou, 2024; Yuviler-Gavish; Halutz; Neta, 2024), suggesting the relationship still needs to be examined in several contexts and settings. Two hypotheses were established regarding the roles of PEOU towards PU and ATT.

H1 : PEOU significantly influences PU

H2 : PEOU significantly influences ATT

2.2 Perceived usefulness (PU)

PU (the degree to which AI will improve their teaching performance) and how these affect ATT and AI-BI in pre-service EFL teachers, in particular, drive the incorporation of AI in the classroom. This study examines two crucial theories investigating these dynamics derived from the TAM (Davis; Bagozzi; Warshaw, 1989). Prior studies revealed that PU is a key component of technology adoption, which directly impacts ATT toward the technology (Gumbi; Sibaya; Chibisa, 2024; Peng; Yan, 2022; Wang; Liu; Tu, 2021; Weng et al., 2018). Gumbi, Sibaya, and Chibisa (2024) who studied pre-service teachers, including those in EFL, revealed that views toward AI tools improve when perceived as helpful for improving student learning outcomes or teaching. However, Wang, Liu, and Tu (2021) disclosed the insignificant relationship between PU and ATT among Chinese teachers on the use of AI in education. PU in this study is also expected to significantly correlate with AI-BI. Pre-service EFL teachers' intention to integrate AI into their teaching practices increases with their perception of the value of technology in accomplishing learning objectives (Al-Abdullatif, 2023; Dehghani; Mashhadi, 2024; Yao; Wang, 2024; Zhang et al., 2023). The correlation suggests that for AI to be successfully included in EFL instruction, it needs to be perceived as directly advancing the learning goals, which will increase motivation to use AI in teaching (Yao; Wang, 2024; Zhang et al., 2023). The two hypotheses show that pre-service EFL teachers' ATT toward AI is influenced, which also strongly influences their desire to include these technologies in their instruction. The elaboration implies that pre-service teacher education programs should emphasize showcasing AI's valuable applications to foster favorable views and intentions regarding its application in classroom environments.

H3 : PU has a significant influence on ATT.

H4 : PU significantly influences AI-BI.

2.3 Attitudes (ATT)

Since ATT can substantially affect how AI is incorporated into future teaching practices, this link is particularly relevant for pre-service EFL teachers. In TAM, ATT frequently serves as the link between perception and action. Prior studies have also revealed the relationship between ATT and behavioral intention to use technology (Allali; Ghouati, 2025; Dehghani; Mashhadi, 2024; Gumbi; Sibaya; Chibisa, 2024; Liu; Ma, 2023; Ma, 2024; Weng *et al.*, 2018; Wu; Wang; Wang, 2023; Zou *et al.*, 2023). Teachers with favorable opinions of AI were likelier to implement these tools in their classes (Gumbi; Sibaya; Chibisa, 2024). Positivity toward AI suggests a willingness to investigate, test, and eventually incorporate new technologies into instructional strategies. One hypothesis was proposed to meet the study's objectives of revealing the correlation between ATT and AI-BI.

H5 : ATT has a positive and significant correlation with AI-BI

2.4 Technological content knowledge (TCK)

TCK in this study refers to pre-service EFL teachers' understanding of how technology can be used in conjunction with particular subject areas. It is hypothesized that TCK significantly influences pre-service EFL teachers' AI-BI; some prior studies have supported a similar hypothesis (An *et al.*, 2023; Habibi; Yusop; Razak, 2020; Mailizar; Hidayat; Al-Manthari, 2021; Sofyan *et al.*, 2023). In a study within the context of English teachers of middle schools in China, An *et al.* (2023) elaborate that teachers are more likely to prepare for using AI when they comprehend how it may interact with language teaching materials. Comprehending how AI enhances content delivery influences teachers' preparedness to integrate these technologies into their curriculum, as language education is content-rich (Habibi; Yusop; Razak, 2020). Further, TCK is a key component of TPACK, which combines content knowledge and technology into a coherent teaching framework. Prior studies have explored the correlations (An *et al.*, 2023; Habibi; Yusop; Razak, 2020; Mailizar; Hidayat; Al-Manthari, 2021; Mansour *et al.*, 2024; Sofyan *et al.*, 2023). For example, Habibi, Yusop, and Razak (2020) state that pre-service language teachers' TCK development directly impacts pre-service teachers' overall TPACK. Understanding how technology interacts with language teaching content (TCK) is essential for EFL teachers to advance their understanding of how to use technology to teach that content (TPACK) (An *et al.*, 2023). The advancement is necessary because language instruction necessitates a sophisticated strategy in which technology complements the teaching methodology and improves the acquisition of linguistic and cultural components. Two hypotheses were proposed to examine TCK's relationship with AI-BI and TPACK.

H6 : TCK significantly influences AI-BI.

H7 : TCK positively and significantly affects TPACK.

2.5 Technological pedagogical knowledge (TPK)

TPK entails comprehending how technology can be used to improve or alter instructional practices, improving the intention to use technology (Voogt *et al.*, 2010). Pre-service teachers' intention to include AI in their teaching practices dramatically increases when they fully understand TPK (An *et al.*, 2023; Habibi; Yusop; Razak, 2020; Mailizar; Hidayat; Al-Manthari, 2021; Sofyan *et al.*, 2023). Teachers are more inclined to embrace new technologies when they understand how AI can be pedagogically integrated to enhance language teaching techniques, such as through tailored learning paths, real-time pronunciation correction, or interactive speaking exercises (An *et al.*, 2023; Habibi; Yusop; Razak, 2020). In addition, TPK is essential to the TPACK framework. TPK directly aids in developing TPACK for pre-service teachers, particularly those in EFL. Knowledge of what to teach (content) and how to utilize technology to teach that material is enhanced and complemented by an understanding of how to teach with technology or TPACK (An *et al.*, 2023; Habibi; Yusop; Razak, 2020; Mailizar; Hidayat; Al-Manthari, 2021; Sofyan *et al.*, 2023). This process requires understanding how AI can be integrated into language instruction to accommodate various learning preferences, linguistic proficiency, and cultural quirks for EFL teachers. Pre-service teachers are able to recognize the comprehensive integration of technology in education, which is a defining characteristic of TPACK, as their TPK grows. We proposed two hypotheses regarding the role of TPK toward AI-BI and TPACK.

H8 : TPK significantly affects AI-BI.

H9 : TPK significantly influences TPACK.

2.6 Technological pedagogical and content knowledge (TPACK)

TPACK thoroughly describes how technology can improve instruction by combining pedagogy, content knowledge, and technology. Pre-service teachers—including those with an EFL concentration—were more likely to indicate plans to include AI in their instruction if they had higher TPACK activities (An et al., 2023; Habibi; Yusop; Razak, 2020; Mailizar; Hidayat; Al-Manthari, 2021; Sofyan et al., 2023). Pre-service teachers' AI-BI toward implementing these technologies rise when they see how AI can be smoothly incorporated into lesson lesson planning, delivering materials, and assessing students (An et al., 2023; Mailizar; Hidayat; Al-Manthari, 2021). To ensure that future educators view AI as an essential component of their teaching toolkit rather than an add-on, this hypothesis emphasizes the necessity for educational programs to cultivate a thorough grasp of TPACK. Further, effective TPACK significantly improves the actual application of AI in education, as expected from the results of the data analysis. Pre-service EFL teachers can put their intentions into practice by learning how to use AI in their teaching strategies, adjusting to the needs of several students, and coordinating technology use with curriculum objectives (An et al., 2023; Habibi; Yusop; Razak, 2020; Mailizar; Hidayat; Al-Manthari, 2021; Sofyan et al., 2023). Teachers who have mastered TPACK are more inventive when creating AI-infused lessons and more adept at resolving issues and adjusting to changing circumstances in the classroom (An et al., 2023; Habibi; Yusop; Razak, 2020; Mailizar; Hidayat; Al-Manthari, 2021). The quality of language instruction is immediately impacted when AI is used for tailored learning paths, language analysis, or cultural immersion experiences, for example, as it becomes more practical and efficient.

H10 : TPACK has a positive and significant impact on AI-BI.

**H11** : TPACK significantly influences AI-USE.

2.7 AI-behavioral intention (AI-BI)

Within the framework of technology acceptance models, notably in educational settings, the connection between intention and actual use has been thoroughly investigated (Lavidas et al., 2024; Strzelecki, 2024; Xiaohong et al., 2024). Strzelecki (2024) who studied the use of ChatGPT in students' learning in higher education disclosed a close correlation between the actual use of AI in learning and a firm intention to employ it. The study implies that for students, when there is a strong desire to use AI—possibly because of the perceived advantages of improving tasks—this desire is likely to materialize in real-world applications such as the use of AI for interactive learning, including language learning and teaching as the context of the current study. A hypothesis was established to reveal the correlation between AI-BI and AI-USE in this study.

H12 : AI-BI significantly affects AI-USE.

3 Method

The current research was conducted through a quantitative approach with a survey as a data collection tool. The survey was selected to gain data that provide a more standardized and consistent evaluation that can be more easily combined and analyzed. This research was conducted from September 2024 to January 2025 using surveys as the data collection method (Ball, 2019; Evans; Mathur, 2005). A review of prior research and an evaluation of the validity and reliability of the instruments were conducted. The model was assessed using partial least squares structural equation modeling (PLS-SEM) (Cepeda et al., 2024; Habibi; Mukminin; Sofyan, 2024; Vaithilingam et al., 2024). The current investigation employed a predictive methodology to ascertain the causality model, as the study's process is unaffected by assumptions on the distribution of data (Habibi; Mukminin; Octavia, et al., 2024). To improve the openness of the study for future replicability, the instrument and samples of the responses can be accessed in Figshare (https://doi.org/10.6084/m9.figshare.28560584).
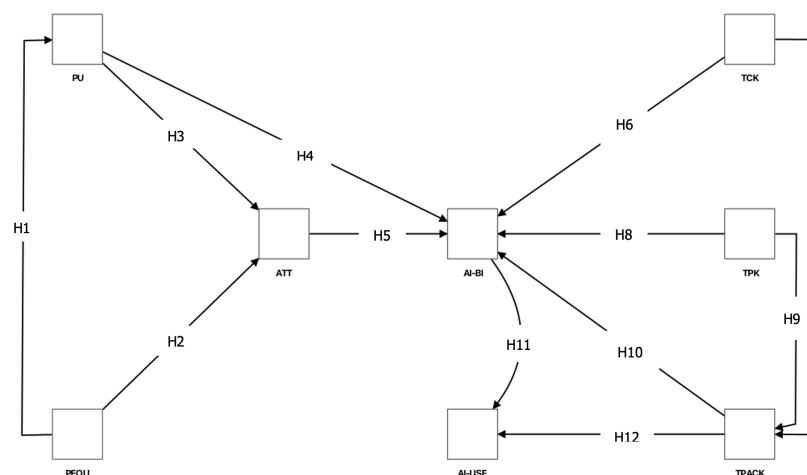
Figure 1. Proposed model
Source: The authors.
Note: Perceived ease of use (PEOU), perceived usefulness (PU), attitudes (ATT), technological content knowledge (TCK), technological pedagogical knowledge (TCK), technological pedagogical content knowledge (TCK), artificial intelligence behavioral intention (AI-BI), artificial intelligence use (AI-USE).

3.1 Instrumentation

The literature review assists a researcher in defining the ideas and concepts within the theoretical framework and identifying suitable methodologies and instruments to achieve the research objectives. We modified and developed survey instruments based on prior related research (50 survey items); TAM (Al-Adwan *et al.*, 2024; Wang; Tan, *et al.*, 2022) and TPACK (Al-Adwan *et al.*, 2024; Habibi; Yusop; Razak, 2020; Mishra; Koehler, 2009). Subsequently, the instruments were evaluated for face and content validity via interviews and the content validity index (CVI) to account for social, cultural, and contextual variations (Oliveira *et al.*, 2022). A panel of six individuals, comprising four pre-service EFL teachers, one program staff members, and one teacher educator, discussed the adapted instruments to assess face validity.

To establish content validity, we consulted five Indonesian experts regarding the instruments. The experts were academics in the domains of educational technology; some items were amended and five items were discarded due to their inapplicability in the academic setting of Indonesia, yielding a total of 45 items for the validation process. The characteristics of the items were evaluated using a 4-point scale (1 = not relevant/not clear/not simple to 4 = extremely relevant, very clear, very simple) by ten experts (Habibi; Yusop; Razak, 2020). The Content Validity Index (CVI) was evaluated at both the item level (I-CVI) and the scale level (S-CVI) for the qualities of the three instruments. The CVI was calculated by assigning a score of 3 or 4 to the experts, then divided by the total number of experts. A score of 3 or 4 in the CVI theory a score of 3 or 4 is considered an affirmative response in CVI theory. The I-CVI must be no less than 0.780 with ten experts (Oliveira *et al.*, 2022). In the computation of the S-CVI, the mean proportion of items on a single scale scored 3 or 4 (average agreement by experts = S-CVI/AVE). The cutoff value is 0.800, and most item values exceed 0.780 for I-CVI and 0.800 for S-CVI.

3.2 Data collection

After completing face, content validity, and CVI assessments, we shared the instruments with the respondents (Rimando *et al.*, 2015). The data were acquired from three Indonesian institutions with education faculties. The data distribution was conducted online using Google Forms. We spent three months collecting the data. all responses were compiled and processed using Microsoft Excel and SPSS. This study's target population comprises all Indonesian pre-service EFL teachers in three institutions or universities. Utilizing stratified sampling, we segmented the target samples based on their universities. In this study, 436 respondents participated in the survey; 22.94% of the respondents

were men and 77.06% were women. Universities A, B, and C accounted for 48.40%, 33.72%, and 17.89%. In the first two semesters, the distribution was 0%; in the third and fourth, 58.94%, and in the fifth and higher, 41.06%. 46.33% of respondents were from cities, and 53.67% were from urban areas. Table 1 exhibits all details of the demographic information included in this study.

Table 1. Demography of the respondents.

Category	n. 436	%
Gender		
Male	100	22.94
Female	336	77.06
Institution		
University A	211	48.40
University B	147	33.72
University C	78	17.89
Semester		
1st-2nd	0	0
3rd-4th	257	58.94
5th-above	179	41.06
School location		
Urban	234	53.67
City	202	46.33

Source: The authors.

3.3 Data preparation

The data preparation in this study aimed to guarantee the completeness and correctness of the data, ensuring the absence of outliers, missing values, and input mistakes. Skewness and kurtosis were evaluated to assess the normality of the data (Miot, 2017; Singh; Masuku, 2014).

3.4 Measurement models

The measurement model involved assessing the reliability and validity of the concept measurements. Four reflecting measurement model indicators (loadings, internal consistency reliability, convergent validity, and discriminant validity) were analyzed in this process (Cepeda *et al.*, 2024; Hair *et al.*, 2024).

4 Findings

The reliability assessment of the current study is essential for validating the measurement models. Data are consistent and trustworthy (Hair *et al.*, 2024; Vaithilingam *et al.*, 2024). Each construct is assessed using four metrics: Cronbach's alpha (α), rho_a, Composite Reliability (CR), and Average Variance Extracted (AVE). Cronbach's alpha quantifies internal consistency, reflecting the interrelatedness among objects (Table 2). The alpha values for all specified constructs vary from 0.815 to 0.907, exceeding the cutoff (0.700), demonstrating strong internal consistency. For example, AI-BI possesses an alpha of 0.815, but TPK exhibits the most significant value of 0.907. This indicates that the instruments employed to assess each construct have high internal consistency. Rho_a is an additional reliability metric that evaluates the construct's dependability based on its factor loadings (Vaithilingam *et al.*, 2024). Good results of the constructs' reliability are indicated by the rho_a values, which range from 0.819 to 0.890. The structures are successfully represented by their respective items, as seen by the rho_a values of 0.819 for AI-BI and 0.890 for TPACK. CR uses the relationships between observed indicator variables to evaluate dependability. From 0.890 for AI-BI to 0.910 for TPK, all CR values are greater than 0.900. The The sufficiently high CR values indicate that the

constructs are reliable. AVE quantifies the proportion of variance in observed variables attributable to the latent component. The ideal AVE score is 0.5 or higher, which indicates that the underlying construct accounts for at least 50% of the variance shown in the items. Robust convergent validity for each construct is confirmed by the AVE values, ranging from 0.643 (AI-USE) to 0.795 (TCK), all surpassing the threshold. With an AVE of 0.795, the TCK shows that the construct accounts for almost 80% of the variance in its components (Habibi; Sofyan; Mukminin, 2023; Teeluckdharry; Teeroovengadum; Seebaluck, 2024).

Table 2. Reliability.

	alpha	rho_a	CR	AVE
AI-BI	0.815	0.819	0.890	0.729
AI-USE	0.907	0.911	0.926	0.643
ATT	0.907	0.909	0.929	0.685
PEOU	0.872	0.876	0.907	0.661
PU	0.887	0.888	0.917	0.689
TCK	0.871	0.873	0.921	0.795
TPACK	0.888	0.890	0.918	0.692
TPK	0.868	0.874	0.910	0.716

Source: The authors.

Factor loadings are vital to validate that each item effectively measures its corresponding construct. For instance, AI-BI1 shows a loading of 0.895 on AI-BI, indicating robust convergent validity. The off-diagonal values represent cross-loadings, which should be lower than the loadings on the intended construct to ensure discriminant validity (Alharbi; Sohaib, 2021; Riady *et al.*, 2025). AI-BI1 exhibits a cross-loading of 0.651 on AI-USE, suggesting a stronger association with AI-BI than with AI-USE (Table 3). The VIF column assists in assessing multicollinearity among constructs, with values near 4 indicating the absence of multicollinearity (Nadella *et al.*, 2024). This comprehensive study is essential for verifying the measuring model, guaranteeing that each construct is measured reliably and distinctively (Cepeda *et al.*, 2024; Hair *et al.*, 2024). All cross-loading values are presented in italics, presented in Table 3.

Heterotrait-Monotrait Ratio of Correlations (HTMT) is crucial for discriminant validity (Habibi; Riady, *et al.*, 2022; Vaithilingam *et al.*, 2024). The HTMT ratio between two constructs is indicated (See Table 4); values less than 0.900 indicate good discriminant validity. AI-BI and AI-USE have an HTMT score of 0.881, which is close to the threshold. With a correlation of 0.700 between AI-USE and ATT, substantial discriminant validity is demonstrated. The uniqueness of both constructs is confirmed by the table's highest value of 0.849 between TCK and TPK, which stays below the conservative threshold. The difference between AI-BI and TCK within the model is further supported by the low value of 0.495 between them. Even though there is a lot of overlap, the HTMT values for PEOU with PU and TPACK are 0.763 and 0.756, respectively, showing that these constructs are still distinct enough for this study.

4.1 Structural model

We used structural model approach through SmartPLS 4.0 to report the correlations among hypothesized variables (Cepeda *et al.*, 2024; Hair *et al.*, 2024). Table 5 displays the path coefficients of each proposed relationshio, t-values, and p-values, offering a thorough overview of the statistical significance. PEOU significantly influences ATT with a path coefficient of 0.387 (t-value $= 5.561$, $p < .001$) and exerts an even more significant effect on PU with a coefficient of 0.674 (t-value $= 17.887$, $p < .001$), indicating that the ease of using AI substantially affects ATT and PU. PU directly affects AI-BI with a coefficient of 0.216 (t-value $= 3.624$, $p < .001$) and ATT with 0.452 (t-value $= 7.311$, $p < .001$), underscoring the significance of perceived advantages of AI in education in shaping ATT and AI-BI. The correlation between ATT and AI-BI exhibits a path coefficient of 0.206 and a t-value

Table 3. Loading, cross-loading, and VIF.

|	AI-BI	AI-USE	ATT	PEOU	PU	TCK	TPACK	TPK	VIF
AI-BI1	*0.855*	0.651	0.479	0.478	0.493	0.362	0.500	0.393	1.810
AI-BI2	*0.865*	0.714	0.477	0.529	0.511	0.376	0.574	0.361	1.782
AI-BI3	*0.841*	0.587	0.510	0.447	0.472	0.331	0.444	0.311	1.794
AI-USE1	0.544	*0.742*	0.488	0.504	0.447	0.325	0.487	0.296	2.001
AI-USE3	0.514	*0.743*	0.491	0.513	0.483	0.283	0.550	0.303	2.105
AI-USE4	0.583	*0.763*	0.534	0.538	0.519	0.301	0.510	0.286	2.085
AI-USE5	0.586	*0.831*	0.503	0.536	0.564	0.327	0.598	0.324	3.363
AI-USE6	0.613	*0.849*	0.523	0.522	0.554	0.321	0.572	0.316	3.513
AI-USE7	0.698	*0.844*	0.503	0.518	0.518	0.395	0.566	0.385	3.021
AI-USE8	0.729	*0.833*	0.520	0.514	0.542	0.380	0.544	0.344	2.648
ATT1	0.464	0.547	*0.861*	0.584	0.603	0.268	0.531	0.313	2.827
ATT2	0.448	0.506	*0.808*	0.549	0.590	0.310	0.513	0.315	2.248
ATT3	0.506	0.554	*0.863*	0.585	0.614	0.331	0.502	0.290	2.937
ATT4	0.491	0.546	*0.874*	0.577	0.623	0.291	0.533	0.279	3.168
ATT5	0.412	0.477	*0.757*	0.589	0.528	0.289	0.519	0.322	1.869
ATT6	0.508	0.511	*0.797*	0.553	0.579	0.291	0.473	0.320	2.017
PEOU1	0.453	0.529	0.579	*0.780*	0.513	0.250	0.493	0.282	1.805
PEOU2	0.494	0.588	0.646	*0.863*	0.611	0.423	0.608	0.414	2.373
PEOU3	0.438	0.482	0.549	*0.843*	0.548	0.268	0.508	0.336	2.352
PEOU4	0.387	0.456	0.487	*0.805*	0.489	0.336	0.559	0.370	2.103
PEOU5	0.535	0.567	0.534	*0.771*	0.566	0.307	0.538	0.291	1.690
PU1	0.462	0.522	0.584	0.513	*0.808*	0.306	0.520	0.280	1.991
PU2	0.487	0.540	0.571	0.577	*0.854*	0.272	0.584	0.267	2.454
PU3	0.482	0.564	0.601	0.557	*0.852*	0.250	0.537	0.270	2.384
PU4	0.426	0.482	0.542	0.573	*0.823*	0.280	0.508	0.281	2.203
PU5	0.528	0.572	0.652	0.574	*0.813*	0.280	0.548	0.267	1.961
TCK1	0.367	0.347	0.282	0.317	0.281	*0.898*	0.434	0.677	2.495
TCK2	0.398	0.402	0.389	0.398	0.340	*0.904*	0.471	0.636	2.470
TCK3	0.352	0.365	0.282	0.331	0.269	*0.873*	0.450	0.655	2.081
TPACK1	0.514	0.611	0.541	0.584	0.538	0.441	*0.847*	0.439	2.271
TPACK2	0.509	0.612	0.537	0.571	0.583	0.380	*0.848*	0.415	2.367
TPACK3	0.511	0.548	0.527	0.534	0.540	0.439	*0.844*	0.460	2.300
TPACK4	0.446	0.476	0.411	0.496	0.489	0.435	*0.780*	0.454	1.837
TPACK5	0.498	0.579	0.546	0.583	0.553	0.416	*0.836*	0.379	2.228
TPK1	0.317	0.318	0.282	0.367	0.278	0.684	0.444	*0.822*	2.005
TPK2	0.344	0.314	0.273	0.293	0.208	0.612	0.354	*0.816*	2.030
TPK3	0.373	0.341	0.336	0.358	0.309	0.566	0.465	*0.869*	2.572
TPK4	0.375	0.387	0.352	0.388	0.307	0.634	0.473	*0.876*	2.630

Source: The authors.

of 2.841, which is statistically significant at $p < .05$, suggesting that a favorable ATT affects the intention to utilize it, albeit with a moderate effect size. TCK exerts minimal influence on AI-BI, evidenced by a path coefficient of 0.094 and a non-significant p-value of 0.103, indicating that expertise in technology within content domains may not directly correlate with utilizing AI in educational practices. TCK substantially influences TPACK with a coefficient of 0.278 (t-value = 4.813, $p < .001$), signifying its essential role in developing a holistic understanding encompassing pedagogy. TPACK strongly predicts AI-BI with a path coefficient of 0.242 (t-value = 3.306, $p < .001$) and AI-USE

Table 4. HTMT.

	AI-BI	AI-USE	ATT	PEOU	PU	TCK	TPACK
AI-BI							
AI-USE	0.881						
ATT	0.665	0.700					
PEOU	0.671	0.728	0.775				
PU	0.675	0.720	0.793	0.763			
TCK	0.495	0.467	0.402	0.446	0.379		
TPACK	0.696	0.758	0.688	0.756	0.732	0.577	
TPK	0.494	0.451	0.415	0.476	0.371	0.849	0.585

Source: The authors.
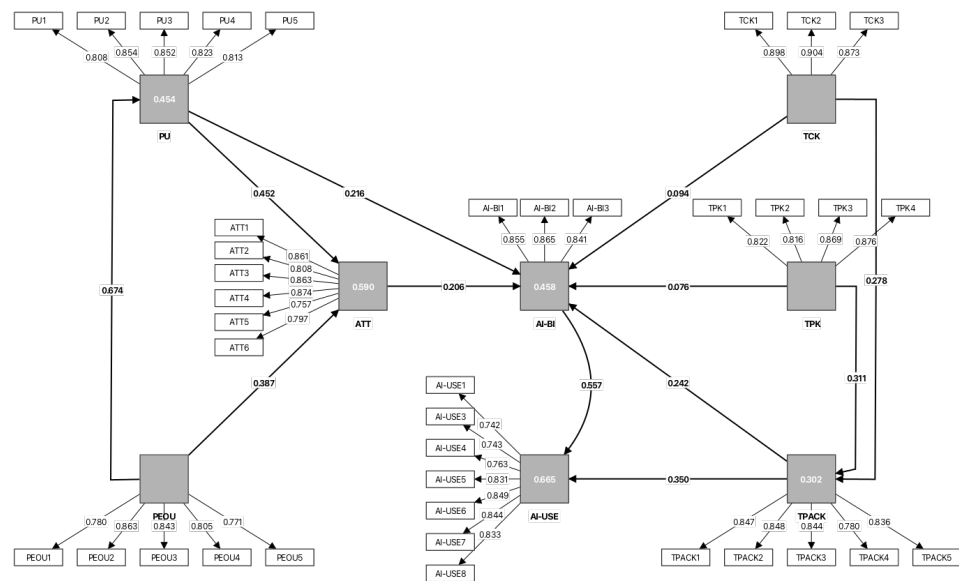

Figure 2. Measurement model.
Source: The authors.

with 0.350 (t-value = 8.251, $p < .001$), underscoring its significance in both intention formation and actual AI utilization. TPK exhibits a path coefficient of 0.076 to AI-BI, which is not statistically significant ($p = 0.172$); however, it significantly influences TPACK with a coefficient of 0.311 (t-value = 4.838, $p < .001$), highlighting its importance in the comprehensive integration of technology into pedagogical practices. The relationship between AI-BI and AI-USE has a path coefficient of 0.557 and a t-value of 12.848, signifying a robust positive influence of behavioral intention on actual AI use, which is statistically significant with a p-value of less than .001.

This comprehensive structural model analysis elucidates the intricate interactions among ATT, perceptions, and types of knowledge for AI use in education, presenting a refined understanding of how these elements can be utilized to improve pre-service EFL teachers' engagement with AI technologies. The prominent pathways and their coefficients indicate areas where interventions may be most impactful, such as augmenting the PEOU of AI tools or strengthening teachers' TPACK to promote broader AI integration in pedagogical practices. The fit indices are as follows: The SRMR is 0.049, signifying a satisfactory match, as values below 0.08 are typically deemed acceptable. The d_ULS score is 1.778, and d_G is 0.826; the metrics evaluate model fit in certain situations, where lower values indicate superior fit. These indices suggest that the model aligns effectively with the data, corroborating the proposed relationships in the study about AI integration in the instruction of pre-service EFL teachers (Magno; Cassia; Ringle, 2022; Schuberth; Rademaker; Henseler, 2023).

Table 5. Structural model.

H	Relationship	β	t-value	p-value	Sign.	Model fit	
H1	PEOU -> PU	0.674	17.887	p <.001	Yes	SRMR	0.049
H2	PEOU -> ATT	0.387	5.561	p <.001	Yes	d_ULS	1.778
H3	PU -> ATT	0.452	7.311	p <.001	Yes	d_G	0.826
H4	PU -> AI-BI	0.216	3.624	p <.001	Yes		
H5	ATT -> AI-BI	0.206	2.841	p <.05	Yes		
H6	TCK -> TPACK	0.278	4.813	p <.00	Yes		
H7	TCK -> AI-BI	0.094	1.628	0.103	No		
H8	TPK -> TPACK	0.311	4.838	p <.001	Yes		
H9	TPK -> AI-BI	0.076	1.366	0.172	No		
H10	TPACK -> AI-BI	0.242	3.306	p <.05	Yes		
H11	TPACK -> AI-USE	0.350	8.251	p <.001	Yes		
H12	AI-BI -> AI-USE	0.557	12.848	p <.001	Yes		

Source: The authors.
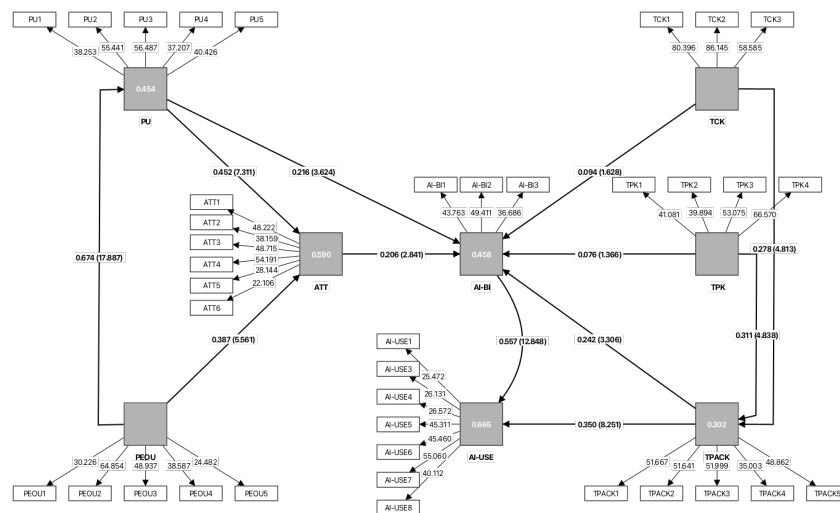
Figure 3. Structural model and R^2.
Source: The authors.

5 Discussion

The current study reports several factors that impact AI behavioral intention (AI-BI) and AI use (AI-USE) among Indonesian pre-service EFL teachers. PEOU significantly influences ATT and PU, with coefficients of 0.387 and 0.674, respectively, both significant at $p < 0.001$. This finding is noteworthy because it highlights the significance of usability in technology adoption, a notion reinforced by prior research from (Dehghani; Mashhadi, 2024), which indicated that in educational technology, ease of use influences ATT and amplifies the perceived utility of the technology. The elevated t-values (5.561 and 17.887) a strong predictive power of PEOU for both constructs, implying that for AI to be integrated into teaching, it must be user-friendly (Al-Abdullatif, 2023; Chen; Zou, 2024; Ma, 2024; Wu; Wang; Wang, 2023; Yuviler-Gavish; Halutz; Neta, 2024).

PU substantially impacts AI-BI and ATT; the results align with the extensions of the TAM by Davis, Bagozzi, and Warshaw (1989), which assert that it is a pivotal factor in technology adoption, particularly in educational settings where the utility of a tool directly influences its acceptability. The strong link between PU and ATT indicates that teachers' perseptions of AI's usefulness greatly influence how they feel about AI (Gumbi; Sibaya; Chibisa, 2024; Peng; Yan, 2022; Wang; Liu; Tu, 2021; Weng *et al.*, 2018). ATT towards AI directly affects AI-BI although the outcome is slightly below expectations; nonetheless. The result aligns with prior reports (Allali; Ghouati, 2025; Dehghani;

Mashhadi, 2024; Ma, 2024), who suggested that although ATT predicts behavioral intention, factors may eclipse its influence in technology adoption frameworks. The significance level indicates that a favorable disposition towards AI does influence the intention to utilize it, albeit potentially less prominently than other aspects.

TCK does not significantly affect AI-BI ($p = 0.103$), which is somewhat unexpected considering the theoretical framework suggesting that technological knowledge should forecast behavioral intents. The result contrasts the result contrasts with prior findings (An $et\ al.$, 2023; Habibi; Yusop; Razak, 2020; Mailizar; Hidayat; Al-Manthari, 2021; Sofyan $et\ al.$, 2023), which indicated that subject understanding directly influences usage intentions unless accompanied by practical experience or training in the realm of swiftly advancing technology such as AI. The lack of significance may indicate a deficiency in the conceptualization or measurement of TCK for the application of AI in education, especially from pre-service EFL teachers. On the other hand, TCK has a substantial impact on TPACK, evidenced by a coefficient of 0.278 ($p < 0.05$), consistent with Mishra and Koehler (2009) TPACK paradigm, which has been further developed by other studies (An $et\ al.$, 2023; Mailizar; Hidayat; Al-Manthari, 2021; Sofyan $et\ al.$, 2023) to incorporate technologies in teaching. The significant contribution of TCK towards TPACK emphasizes that comprehending information through technological perspectives is essential for integrating AI into educational procedures. Ultimately, TPK demonstrates a substantial correlation with TPACK (0.311, $p < 0.001$) but lacks a meaningful association with AI-BI ($p = 0.172$). The computation of the data might suggest that although TPK is essential for comprehending the enhancement of education through technology, it may not directly affect the desire to utilize AI until included in a more comprehensive knowledge structure such as TPACK (An $et\ al.$, 2023; Habibi; Yusop; Razak, 2020; Mailizar; Hidayat; Al-Manthari, 2021; Mansour $et\ al.$, 2024).

The substantial correlation with TPACK indicates that TPK enhances the comprehension of AI's role in education. TPACK significantly influences AI-BI and AI-USE, supporting prior reports (An $et\ al.$, 2023; Habibi; Yusop; Razak, 2020; Mailizar; Hidayat; Al-Manthari, 2021; Mansour $et\ al.$, 2024; Sofyan $et\ al.$, 2023). Teachers with a profound comprehension of the interplay between technology, pedagogy, and content are likelier to embrace and utilize AI in their instruction. The impact on AI-USE is especially significant, indicating that TPACK motivates intention and facilitates actual implementation. The association between AI-BI and AI-USE is characterized by a path coefficient of 0.557, signifying a robust and statistically significant positive correlation. This discovery corresponds with prior studies, which examined the incorporation of AI in educational environments and determined that the intention to utilize AI is a strong predictor of its actual application by educators (Barjestesh $et\ al.$, 2025; Baskara $et\ al.$, 2024; Lavidas $et\ al.$, 2024; Raman; Hashim; Ismail, 2023; Strzelecki, 2024; Xiaohong $et\ al.$, 2024). The strong t-value indicates that Indonesian pre-service EFL teachers are more likely to use AI in their instruction when they plan to use the technology.

The structured model illustrates the intricate interaction of factors affecting pre-service EFL teachers' AI adoption. AI must be user-friendly and valuable to be successfully integrated into education, as PEOU and PU are major determinants across numerous parameters. Further research on AI knowledge structure operationalization is needed for the non-significant pathways TCK and TPK to AI-BI, suggesting that practical experience or targeted training may be required to address these issues. Technology, pedagogy, and content must be understood to increase AI adoption since TPACK affects intention and use. Our findings enhance the literature on AI in education, provide a detailed view of technology adoption patterns among potential educators, and recommend future research and policy improvements to integrate AI into teaching.

6 Conclusion

The current study's findings show that perceived ease of use and perceived usefulness are crucial to attitudes, AI behavioral intention, and AI use with strong coefficients. For AI to be used in education, it must be user-friendly and must be user-friendly and pedagogically beneficials. Based on the findings, educational technology must also be accessible and beneficial to boost EFL uptake. The strong links between TPACK, AI behavioral intention, and AI use present the need to combine technology experience with pedagogical and content knowledge. Technological pedagogical and content

knowledge is significant, demonstrating that a thorough understanding of integrating AI into teaching techniques increases the intention to use AI in education. Non-significant paths like technological content knowledge to AI behavioral intention and technological pedagogical knowledge to AI behavioral intention suggest areas of poor comprehension or execution requiring further conceptual clarity or practical refinement. Understanding technology and its pedagogical effects is essential, but without technological pedagogical and content knowledge, it may not directly influence AI use. Practical EFL instruction that links academic understanding to real-world application may be needed.

Given these findings, educational institutions and policymakers ought to enhance EFL teacher training programs by incorporating specialized modules on AI, highlighting usability and utility, and integrating technology with pedagogy and content. Future studies may investigate why specific knowledge components fail to directly impact AI-BI, examining whether experiential learning or targeted AI training could enhance these relationships. Furthermore, longitudinal research could evaluate the evolution of these interactions as educators accumulate experience with AI, offering a dynamic perspective on technology adoption across time. This study enhances the conversation on AI in education by providing empirical information regarding the factors that promote or obstruct AI adoption among pre-service EFL teachers. A deliberate approach to teacher education is required to convey knowledge and guarantee its practical application, cultivating a generation of educators prepared to utilize AI to improve their teaching effectiveness and student learning results.

References

AL-ABDULLATIF, A. M. Modeling Students' Perceptions of Chatbots in Learning: Integrating Technology Acceptance with the Value-Based Adoption Model. *Education Sciences*, v. 13, n. 11, 2023.

AL-ADWAN, A. S.; MEET, R. K.; ANAND, S.; SHUKLA, G. P.; ALSHARIF, R.; DABBAGHIA, M. Understanding continuous use intention of technology among higher education teachers in emerging economy: evidence from integrated TAM, TPACK, and UTAUT model. *Studies in Higher Education*, p. 1–20, Apr. 2024.

ALHARBI, A.; SOHAIB, O. Technology Readiness and Cryptocurrency Adoption: PLS-SEM and Deep Learning Neural Network Analysis. *IEEE Access*, v. 9, 2021.

ALLALI, S.; GHOUATI, A. EFL Classroom: Teachers' Perceptions and Intention to Use ChatGPT for Language Teaching. *Journal of Applied Language and Culture Studies*, 2025. Available from: https://revues.imist.ma/index.php?journal=JALCS.

AN, X.; CHAI, C. S.; LI, Y.; ZHOU, Y.; SHEN, X.; ZHENG, C.; CHEN, M. Modeling English teachers' behavioral intention to use artificial intelligence in middle schools. *Education and Information Technologies*, v. 28, n. 5, 2023.

BALL, H. L. Conducting Online Surveys. *Journal of Human Lactation*, v. 35, n. 3, 2019.

BARJESTESH, H.; VIJAYARATNAM, P.; SABZEVARI, M.; RAD, N. F.; RABANI, K.; MANOOCHEHRZADEH, M. Digital Literacy of Iranian English as a Foreign Language (EFL) Teachers: Teaching Experience in Focus. *Forum for Linguistic Studies*, v. 7, n. 1, p. 163–171, 2025.

BASKARA, F. X. R.; VASUDEVAN, A.; SAIN, Z. H.; TEE, M.; ARUMUGAM, V.; PARAHAKARAN, S. S.; BALAKRISHNAN, R. Redefining educational paradigms: Integrating generative AI into society 5.0 for sustainable learning outcomes. *Journal of Infrastructure, Policy and Development*, v. 8, n. 12, p. 6385, 2024.

CEPEDA, G.; ROLDÁN, J. L.; SABOL, M.; HAIR, J.; CHONG, A. Y. L. Emerging opportunities for information systems researchers to expand their PLS-SEM analytical toolbox. *Industrial Management & Data Systems*, v. 124, n. 6, p. 2230–2250, June 2024.

CHEN, Y.; ZOU, Y. Enhancing education quality: Exploring teachers' attitudes and intentions towards intelligent MR devices. *European Journal of Education*, v. 59, n. 4, Dec. 2024.

CHENG, J.; HALL, J. A.; WANG, Q.; LEI, J. More than high, medium, and low: Pre-service teacher TPACK profiles and intentions to teach with technology. *Education and Information Technologies*, v. 29, n. 18, p. 24387–24413, Dec. 2024.

DARWIN; RUSDIN, D.; MUKMINATIEN, N.; SURYATI, N.; LAKSMI, E. D.; MARZUKI. Critical thinking in the AI era: An exploration of EFL students' perceptions, benefits, and limitations. *Cogent Education*, v. 11, n. 1, 2024.

DAVIS, F. D.; BAGOZZI, R. P.; WARSHAW, P. R. User Acceptance of Computer Technology: A Comparison of Two Theoretical Models. *Management Science*, v. 35, n. 8, p. 982–1003, 1989.

DEHGHANI, H.; MASHHADI, A. Exploring Iranian English as a Foreign Language Teachers' Acceptance of ChatGPT in English Language Teaching: Extending the Technology Acceptance Model. *Education and Information Technologies*, v. 29, n. 15, p. 19813–19834, Oct. 2024.

EVANS, J. R.; MATHUR, A. The value of online surveys. *Internet Research*, v. 15, n. 2, p. 195–219, 2005.

GUMBI, N. M.; SIBAYA, D.; CHIBISA, A. Exploring Pre-Service Teachers' Perspectives on the Integration of Digital Game-Based Learning for Sustainable STEM Education. *Sustainability (Switzerland)*, v. 16, n. 3, 2024.

HABIBI, A.; MUKMININ, A.; OCTAVIA, A.; WAHYUNI, S.; DANIBAO, B. K.; WIBOWO, Y. G. ChatGPT acceptance and use through UTAUT and TPB: A big survey in five Indonesian Universities. *Social Sciences & Humanities Open*, v. 10, p. 101136, 2024.

HABIBI, A.; MUKMININ, A.; SOFYAN, S. Access to the digital technology of urban and suburban vocational schools. *Education and Information Technologies*, v. 29, n. 4, 2024.

HABIBI, A.; RIADY, Y.; SAMED AL-ADWAN, A.; AWNI ALBELBISI, N. Beliefs and Knowledge for Pre-Service Teachers' Technology Integration during Teaching Practice: An Extended Theory of Planned Behavior. *Computers in the Schools*, 2022.

HABIBI, A.; SOFYAN, S.; MUKMININ, A. Factors affecting digital technology access in vocational education. *Scientific Reports*, v. 13, n. 1, p. 5682, Dec. 2023.

HABIBI, A.; YAAKOB, M. F. M.; AL-ADWAN, A. S. m-Learning Management System use during Covid-19. *Information Development*, 2023.

HABIBI, A.; YUSOP, F. D.; RAZAK, R. A. The role of TPACK in affecting pre-service language teachers' ICT integration during teaching practices: Indonesian context. *Education and Information Technologies*, v. 25, n. 3, p. 1929–1949, 2020.

HAIR, J. F.; SHARMA, P. N.; SARSTEDT, M.; RINGLE, C. M.; LIENGAARD, B. D. The shortcomings of equal weights estimation and the composite equivalence index in PLS-SEM. *European Journal of Marketing*, v. 58, n. 13, 2024.

LAVIDAS, K.; VOULGARI, I.; PAPADAKIS, S.; ATHANASSOPOULOS, S.; ANASTASIOU, A.; FILIPPIDI, A.; KOMIS, V.; KARACAPILIDIS, N. Determinants of Humanities and Social Sciences Students' Intentions to Use Artificial Intelligence Applications for Academic Purposes. *Information*, v. 15, n. 6, p. 314, May 2024.

LIU, G.; MA, C. Measuring EFL learners' use of ChatGPT in informal digital learning of English based on the technology acceptance model. *Innovation in Language Learning and Teaching*, 2023.

MA, M. Exploring the acceptance of generative artificial intelligence for language learning among EFL postgraduate students: An extended TAM approach. *International Journal of Applied Linguistics*, Aug. 2024.

MAGNO, F.; CASSIA, F.; RINGLE, C. M. M. A brief review of partial least squares structural equation modeling (PLS-SEM) use in quality management studies. *TQM Journal*, 2022.

MAILIZAR, M.; HIDAYAT, M.; AL-MANTHARI, A. Examining the impact of mathematics teachers' TPACK on their acceptance of online professional development. *Journal of Digital Learning in Teacher Education*, v. 37, n. 3, 2021.

MANSOUR, N.; SAID, Z.; ÇEVIK, M.; ABU-TINEH, A. Science and Mathematics Teachers' Integration of TPACK in STEM Subjects in Qatar: A Structural Equation Modeling Study. *Education Sciences*, v. 14, n. 10, p. 1138, Oct. 2024.

MIOT, H. A. Assessing normality of data in clinical and experimental trials. *Jornal Vascular Brasileiro*, v. 16, n. 2, 2017.

MISHRA, P.; KOEHLER, M. Using the TPACK Framework. *Learning & Leading with Technology*, v. 36, n. 7, p. 14–18, 2009.

NADELLA, G. S.; MEDURI, K.; SATISH, S.; MATURI, M. H.; GONAYGUNTA, H. Examining E-learning tools impact using IS-impact model: A comparative PLS-SEM and IPMA case study. *Journal of Open Innovation: Technology, Market, and Complexity*, v. 10, n. 3, p. 100351, Sept. 2024.

OLIVEIRA, M. K. de M.; KAIZER, U. A. de O.; JANNUZZI, F. F.; GALLANI, M. C.; ALEXANDRE, N. M. C.; CORNÉLIO, M. E.; SÃO-JOÃO, T. M.; RODRIGUES, R. C. M. Content Validity of a Questionnaire Based on the Theory of Planned Behavior to Assess the Psychosocial Determinants of Insulin Adherence. *Value in Health Regional Issues*, v. 29, 2022.

PENG, M. Y. P.; YAN, X. Exploring the Influence of Determinants on Behavior Intention to Use of Multiple Media Kiosks Through Technology Readiness and Acceptance Model. *Frontiers in Psychology*, v. 13, 2022.

RAMAN, K.; HASHIM, H.; ISMAIL, H. H. Enhancing English Verbal Communication Skills through Virtual Reality: A Study on Engagement, Motivation, and Autonomy among English as a Second Language Learners. *International Journal of Learning, Teaching and Educational Research*, v. 22, n. 12, p. 237–261, 2023.

RIADY, Y.; HABIBI, A.; MAILIZAR, M.; ALQAHTANI, T. M.; RIADY, H.; AL-ADWAN, A. S. TAM and IS success model on digital library use, user satisfaction and net benefits: Indonesian open university context. *Library Management*, Jan. 2025.

RIMANDO, M.; BRACE, A. M.; NAMAGEYO-FUNA, A.; PARR, T. L.; SEALY, D. A. Data collection challenges and recommendations for early career researchers. *Qualitative Report*, v. 20, n. 12, p. 2025–2036, 2015.

SCHUBERTH, F.; RADEMAKER, M. E.; HENSELER, J. Assessing the overall fit of composite models estimated by partial least squares path modeling. *European Journal of Marketing*, v. 57, n. 6, 2023.

SINGH, A. S.; MASUKU, M. B. Normality and Data Transformation for Applied Statistical Analysis. *International Journal of Economics, Commerce and Management*, v. 2, n. 7, 2014.

SOFYAN, S.; HABIBI, A.; SOFWAN, M.; YAAKOB, M. F. M.; ALQAHTANI, T. M.; JAMILA, A.; WIJAYA, T. T. TPACK–UotI: the validation of an assessment instrument for elementary school teachers. *Humanities and Social Sciences Communications*, v. 10, n. 1, p. 55, Feb. 2023.

STRZELECKI, A. Students' Acceptance of ChatGPT in Higher Education: An Extended Unified Theory of Acceptance and Use of Technology. *Innovative Higher Education*, v. 49, n. 2, p. 223–245, Apr. 2024.

SUN, F.; TIAN, P.; SUN, D.; FAN, Y.; YANG, Y. Pre-service teachers' inclination to integrate AI into STEM education: Analysis of influencing factors. *British Journal of Educational Technology*, v. 55, n. 6, p. 2574–2596, Nov. 2024.

TEELUCKDHARRY, N. B.; TEEROOVENGADUM, V.; SEEBALUCK, A. K. A roadmap for the application of PLS-SEM and IPMA for effective service quality improvements. *TQM Journal*, v. 36, n. 5, 2024.

THOHIR, M. A.; AHDHIANTO, E.; MAS'ULA, S.; YANTI, F. A.; SUKARELAWAN, M. I. The effects of TPACK and facility condition on preservice teachers' acceptance of virtual reality in science education course. *Contemporary Educational Technology*, v. 15, n. 2, 2023.

VAITHILINGAM, S.; ONG, C. S.; MOISESCU, O. I.; NAIR, M. S. Robustness checks in PLS-SEM: A review of recent practices and recommendations for future applications in business research. *Journal of Business Research*, v. 173, 2024.

VENKATESH, V. Adoption and use of AI tools: a research agenda grounded in UTAUT. *Annals of Operations Research*, v. 308, n. 1–2, 2022.

VOOGT, J. *et al.* Strategies for teacher professional development on TPACK, Part 2. *In:* PROCEEDINGS of Society for Information Technology Teacher Education International Conference 2010. [*S. l.: s. n.*], 2010. Disponível em: http://www.mendeley.com/research/strategies-teacher-professional-development-tpack/.

WANG, G.; TAN, G. W. H.; YUAN, Y.; OOI, K. B.; DWIVEDI, Y. K. Revisiting TAM2 in behavioral targeting advertising: A deep learning-based dual-stage SEM-ANN analysis. *Technological Forecasting and Social Change*, v. 175, 2022.

WANG, Y.; LIU, C.; TU, Y. F. Factors Affecting the Adoption of AI Based Applications in Higher Education: An Analysis of Teachers Perspectives Using Structural Equation Modeling. *Educational Technology and Society*, v. 24, n. 3, 2021.

WENG, F.; YANG, R. J.; HO, H. J.; SU, H. M. A TAM-based study of the attitude towards use intention of multimedia among school teachers. *Applied System Innovation*, v. 1, n. 3, 2018.

WU, H.; WANG, Yunsong; WANG, Yongliang. "To Use or Not to Use?" A Mixed-Methods Study on the Determinants of EFL College Learners' Behavioral Intention to Use AI in the Distributed Learning Context. *International Review of Research in Open and Distributed Learning*, 2023. [s.l.: s.n.]

XIAOHONG, L.; JUN, Z.; XIAOMING, C.; BEINA, Z. A study on behavioral intentions of artificial intelligence learning platform: comparing the perspectives of teachers and students. *Interactive Learning Environments*, p. 1–21, Apr. 2024.

YAO, N.; WANG, Q. Factors influencing pre-service special education teachers' intention toward AI in education: Digital literacy, teacher self-efficacy, perceived ease of use, and perceived usefulness. *Heliyon*, v. 10, n. 14, e34894, July 2024.

YOON, S. J.; KIM, M. Y. A Study on the Improvement Direction of Artificial Intelligence Speakers Applying DeLone and McLean's Information System Success Model. *Human Behavior and Emerging Technologies*, 2023.

YUVILER-GAVISH, N.; HALUTZ, R.; NETA, L. How whatsappization of the chatbot affects perceived ease of use, perceived usefulness, and attitude toward using in a drive-sharing task. *Computers in Human Behavior Reports*, v. 16, Dec. 2024.

ZHANG, C.; SCHIESSL, J.; PLÖSSL, L.; HOFMANN, F.; GLÄSER-ZIKUDA, M. Acceptance of artificial intelligence among pre-service teachers: a multigroup analysis. *International Journal of Educational Technology in Higher Education*, v. 20, n. 1, 2023.

ZOU, B.; LYU, Q.; HAN, Y.; LI, Z.; ZHANG, W. Exploring students' acceptance of an artificial intelligence speech evaluation program for EFL speaking practice: an application of the Integrated Model of Technology Acceptance. *Computer Assisted Language Learning*, 2023.

Author contributions