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Trends in Research Methods

Applying AI For English Language Instruction and Material Development in Schools: A PLS-SEM Approach

Lastika Ary Prihandoko
Universitas Sebelas Maret, Indonesia

Suci Nugrah Amalia
Universitas Negeri Malang, Indonesia

Priyatno Ardi
Universitas Sanata Dharma, Indonesia

Budi Waluyo*
Walailak University, Thailand

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Abstract
Despite growing recognition of the value of artificial intelligence (AI) in English as a Foreign Language (EFL) instruction, adoption at the school level remains limited due to a lack of understanding about the complex factors influencing teachers' post-training acceptance. This study examined the interrelationships among subjective norms, technologist roles, student influence, process facilitation, compatibility, perceived attitudes, and behavioral intentions in Indonesian senior high school EFL teachers following a professional development workshop on AI integration. Using validated survey instruments, data from 146 teachers were analyzed with Partial Least Squares Structural Equation Modeling (PLS-SEM) and Importance-Performance Matrix Analysis (IPMA). Quantitative results showed that subjective norms significantly affected process facilitation and compatibility, while student influence strongly predicted technologist roles, compatibility, and process facilitation. Technologist roles and compatibility were pivotal in shaping positive attitudes and intentions to adopt AI. IPMA identified compatibility as a key area for targeted improvement. The findings stress the need for ongoing, context-sensitive professional development to promote effective and sustainable AI integration in EFL teaching.

Keywords
Artificial intelligence, EFL, material development, language instruction, PLS-SEM analysis

*Corresponding author. Email: budi.business.waluyo@gmail.com

1 Introduction

Across sectors, digital technologies have rapidly reshaped work and learning, and education systems in many countries are integrating artificial intelligence (AI) into curriculum design, assessment, adaptive tutoring, and school operations. However, despite this global momentum, classroom-level adoption remains uneven and often stalls without sustained infrastructure, policy support, and teacher readiness (Bower et al., 2020; Mason et al., 2020; Yang et al., 2024). Within this wider trend, the integration of AI in English as a Foreign Language (EFL) instruction is widely recognized as essential, yet its practical adoption at the school level remains limited (Seo et al., 2024; Simatupang et al., 2025). Effective adoption depends on EFL teachers' behavioral intentions, shaped by factors such as subjective norms and technological competencies (Ebneyamini & Sadeghi Moghadam, 2018; Teng & Yip, 2025; Sanusi et al., 2024). Although positive intentions can foster curriculum innovation and personalized learning (Bower et al., 2020), many institutions still face constraints in infrastructure, ongoing professional development, and clear guidelines for integrating AI into curricula (Simatupang et al., 2025). Teacher readiness also varies, influenced by demographic factors, technological anxiety, and institutional culture, leading to inconsistent uptake. Existing research often isolates individual predictors, overlooking the interplay of social, technical, and pedagogical factors shaping post-training adoption. Thus, understanding the critical determinants of AI adoption becomes fundamental for developing frameworks that equip teachers with requisite technical competencies and facilitate long-term pedagogical transformation aligned with evolving digital literacies. Without such targeted and evidence-based strategies, AI integration risks remaining superficial and unsustainable.

EFL teachers' intentions to embrace AI technology are influenced primarily by performance expectancy, effort expectancy, and social influence, core elements of established technology acceptance models (An et al., 2023; Zhang & Dikilitaş, 2025). While these constructs are widely used in research, many teachers may not be explicitly familiar with the terminology; instead, they experience them in practice, for example, by considering whether AI will genuinely improve their teaching (performance expectancy), whether it will be easy to use (effort expectancy), and how peers or institutional culture may shape their adoption decisions (social influence). The AI-TPACK framework integrates these predictors with pedagogical content knowledge, effectively linking technological capabilities with disciplinary expertise and pedagogical practices, crucial for successful AI adoption (Ning et al., 2024). Nevertheless, acceptance is also mediated by demographic variables such as age and technological anxiety, with younger teachers often more willing to adopt AI than older colleagues. Given the rapid global integration of AI in education, understanding these variations is critical. Although research has advanced our knowledge of AI acceptance, most studies isolate individual predictors and overlook how they interact after hands-on training, particularly in EFL contexts where adoption is shaped by teacher roles, student expectations, and institutional norms. This study addresses the gap by adopting a comprehensive framework that integrates subjective norms, technologist roles, and student influences. Using Partial Least Squares Structural Equation Modeling (PLS-SEM) and Importance–Performance Matrix Analysis (IPMA), it examines key interrelationships and identifies strategic priorities, offering both theoretical insights and practical guidance for AI adoption in EFL education.

Specifically, this study explores the factors that influence EFL teachers' adoption of artificial intelligence (AI) in language education and how these factors interact after professional development workshops. The key variables include subjective norms, technologist roles, student influence, process facilitation, compatibility, perceived attitudes, and behavioral intention. Grounded in the Unified Theory of Acceptance and Use of Technology (UTAUT) and the Diffusion of Innovations (DOI) theory, the research examines how social, technological, and pedagogical elements combine to shape teachers' readiness and continued engagement with AI tools. Integrating these two frameworks enables the study to develop a comprehensive model that connects behavioral intention with the diffusion of innovation, highlighting how teachers make decisions about AI integration. The study employs Partial Least Squares

Structural Equation Modeling (PLS-SEM) to examine both measurement and structural relationships, an approach well-suited for complex models with multiple latent variables and relatively small sample sizes. To complement this, Importance–Performance Matrix Analysis (IPMA) identifies which constructs are most influential yet underperforming, thereby offering practical recommendations for improving professional development and policy strategies that promote sustainable AI integration in EFL contexts.

2 Literature Review

2.1 Subjective norms

Subjective norms represent the perceived social pressures influencing an individual's behavioral intentions, as articulated in the Theory of Planned Behavior (Ajzen, 2012). In educational contexts, particularly within English as a Foreign Language (EFL) teaching, subjective norms manifest through the expectations and encouragement from key institutional actors such as colleagues, administrators, and policymakers (Ebneyamini & Sadeghi Moghadam, 2018; Sanusi et al., 2024). According to the Unified Theory of Acceptance and Use of Technology (UTAUT), social influence from peers and leadership plays a pivotal role in determining technology adoption by enhancing perceived legitimacy and reducing uncertainties associated with innovative pedagogical tools (Venkatesh et al., 2003; Wang et al., 2017). Nonetheless, existing literature primarily focuses on the direct influence of subjective norms on initial intention formation, thereby neglecting their broader implications for teachers' roles, such as the development of technological identity and compatibility perceptions in teaching practices.

To address this gap, the current study extends the conceptualization of subjective norms beyond mere intention formation, proposing that subjective norms significantly influence teachers' roles in facilitating the learning process, shaping their technological identities, and determining perceived compatibility with existing instructional practices. Teachers are more likely to adopt novel technologies such as AI when they perceive strong institutional support, suggesting a conducive social environment may enhance their role in facilitating processes of instructional innovation (Ebneyamini & Sadeghi Moghadam, 2018). Yet, social influence alone may be insufficient to establish teachers' technological identities, as the development of such identities requires sustained internal motivation and contextually relevant skill-building (Sanusi et al., 2024). Therefore, while subjective norms can initiate the exploration of technology, enduring adoption necessitates alignment with practical classroom demands and teachers' professional competencies.

Based on these arguments, the following hypotheses are formulated:

- H1a: Subjective Norms positively influence the Process facilitator role.
- H1b: Subjective Norms enhance perceptions of AI as a Technologist tool.
- H1c: Subjective Norms increase Compatibility with existing teaching practices.

2.2 Technologist roles

The adoption of artificial intelligence (AI) in language education redefines the role of EFL teachers, requiring them to evolve into dual-role professionals who balance language instruction with technological integration. Research on technology-enhanced language learning consistently shows that teachers who demonstrate strong technological competencies are more capable of integrating digital tools to support instructional objectives, foster student engagement, and improve learning outcomes (Zakaria & Hashim, 2024). In the context of AI, such competencies are crucial for selecting appropriate tools, adapting them to curriculum needs, and creating technology-mediated learning experiences that are both effective and sustainable. Studies also indicate that the ability to integrate AI effectively is often linked to teachers' confidence in their technological skills and their willingness to experiment with innovative practices, even in the face of infrastructural or pedagogical challenges (Celik, 2023). Nevertheless, the specific implications of the technologist role within EFL contexts remain inadequately explored, especially regarding its influence on the compatibility of new technological tools with established instructional methods and the subsequent effects on teachers' roles as facilitators.

Despite the recognized benefits of AI tools, teachers frequently encounter significant obstacles in integrating these technologies effectively into their existing instructional frameworks (Celik, 2023). Central to addressing this challenge is the development of robust technological competencies, which empower teachers to meaningfully align AI functionalities with pedagogical and curricular demands. This technological proficiency not only enhances the perceived compatibility of AI tools but also reinforces teachers' confidence and capabilities in their roles as facilitators of innovative learning processes. Consequently, the technologist role emerges as an essential component in achieving sustained, meaningful technology adoption within classroom practices. Informed by TPACK, this study positions the technologist role as a critical predictor of AI adoption outcomes, particularly in enhancing perceived compatibility of AI tools and strengthening teachers' capacity to act as process facilitators in technology-rich learning environments.

Accordingly, this study hypothesizes:

- H2a: Being a Technologist positively influences Compatibility with AI tools.
- H2b: The Technologist role enhances the Process facilitator role.

2.3 Student influence

Student influence constitutes a critical but often under-examined element within technology adoption models in educational settings. Traditionally, adoption frameworks have primarily considered teacher-centric factors, overlooking students' active roles in shaping instructional practices (Kim, Lee, & Cho, 2022). However, from a sociocultural perspective (Vygotsky, 1978), students significantly impact classroom dynamics by actively engaging with new educational tools and providing immediate feedback that guides teachers' instructional decisions (Elahi Shirvan et al., 2021). Students' readiness and enthusiasm for digital tools often exceed those of their teachers, creating a dynamic where students' digital proficiency and engagement motivate teachers to experiment with and integrate AI technologies into teaching practices (Waluyo & Kusumastuti, 2024).

The reciprocity inherent in this student-teacher interaction suggests that students' behaviors and technological competencies directly shape teachers' self-perceptions as capable technology users. Specifically, students' familiarity and enthusiasm regarding AI tools reinforce teachers' confidence, prompting teachers to assume a more active technologist identity, facilitating increased compatibility with AI-based instructional methods, and strengthening their roles in guiding AI-supported learning processes. Such dynamics underscore the socially situated nature of AI adoption, highlighting students not merely as passive beneficiaries but active agents in influencing instructional innovation and teacher role transformation.

Thus, the study proposes the following hypotheses:

- H3a: Student influence positively affects the Technologist role.
- H3b: Student influence enhances Compatibility with AI tools.
- H3c: Student influence strengthens the Process facilitator role.

2.4 Process facilitator role

The process facilitator role positions EFL teachers as central intermediaries, responsible for the coherent integration of AI into instructional methods while simultaneously guiding students and refining their professional and technological competencies. Within the TPACK framework, Ning et al. (2024) assert that effective facilitation demands the strategic alignment of content knowledge, pedagogical practices, and technological resources to foster enriched learning environments. Empirical evidence suggests that teachers adopting facilitator roles, rather than traditional transmitter roles, demonstrate greater adaptability and confidence in managing digitally mediated learning scenarios, which subsequently enhances instructional effectiveness and student engagement (Guggemos & Seufert, 2021; Holstein, McLaren, & Aleven, 2019).

Despite these insights, existing research often narrowly examines AI effectiveness in terms of student outcomes, neglecting the essential role that facilitation plays in shaping teachers' ongoing professional development and attitudes toward technology (Boubker, 2024). To bridge this gap, this research conceptualizes facilitative practices as dual mechanisms: they simultaneously enhance teachers' competencies with AI tools and foster positive attitudes towards technology. Facilitative teaching thus represents both an instructional strategy and a professional development pathway, integral to creating emotionally positive, confident, and technologically fluent educators.

Accordingly, the following hypotheses are proposed:

• H4a: Process facilitation leads to Competency building in AI usage.

• H4b: Process facilitation positively affects Perceived attitudes towards AI.

2.5 Compatibility

Compatibility, defined as the extent to which AI tools align with existing teaching practices, curricular goals, and instructional values, is a crucial factor influencing technology adoption in educational settings (Chen, 2011; Venkatesh et al., 2003). Enhanced compatibility reduces integration barriers and boosts perceived usefulness, thereby facilitating sustainable adoption of AI within classroom contexts. Nevertheless, existing literature frequently treats compatibility superficially, neglecting its potential developmental impact on teachers' professional growth and attitudinal changes toward educational innovation (Schlager & Fusco, 2003).

Recognizing compatibility as both a functional enabler and a psychological motivator, this study explicitly examines how perceived compatibility influences teachers' competency development and attitudes toward AI integration. Compatibility facilitates smoother integration and sustains pedagogical innovation by aligning AI tools with teachers' instructional routines, thereby promoting long-term usage and positive attitudinal shifts toward new educational technologies.

Based on these arguments, the study hypothesizes:

• H5a: Compatibility with existing practices facilitates Competency building.

• H5b: Compatibility enhances Perceived attitudes towards AI.

2.6 Behavioral intention

Behavioral intention, defined as an individual's readiness to perform a specific future action, is pivotal within technology acceptance frameworks such as the Technology Acceptance Model (TAM) and UTAUT (Venkatesh et al., 2003). In the context of EFL education, behavioral intention signifies teachers' commitment to sustain AI usage beyond initial exposure. Prior research emphasizes the significance of perceived utility and ease of use as primary determinants of behavioral intention (Kim et al., 2022; Yue et al., 2024). However, extant literature insufficiently addresses how these intentions evolve following professional development programs, particularly considering the interplay of competency building and attitude formation.

Addressing this critical research gap, this study proposes that sustained behavioral intention emerges from the synergistic interaction of competency acquisition and positive attitudinal development. Effective, long-term AI adoption necessitates that teachers not only perceive AI tools as valuable but also possess the practical skills required to integrate these tools effectively into their daily instructional practices.

Therefore, this study hypothesizes:

- H6a: Perceived attitudes towards AI predict Behavioral intentions.
- H6b: Competency building predicts Behavioral intentions.

Table 1 below summarizes the theoretical foundations, key references, and corresponding hypotheses for each construct investigated in this study. This synthesis not only clarifies the conceptual underpinnings of the research model but also demonstrates how each hypothesis is grounded in existing literature and aligned with established educational and technological theories.

Table 1

Summary of Constructs, Theoretical Frameworks, and Associated Hypotheses

Construct	**Theoretical Foundation**	**Key References**	**Related Hypotheses**
Subjective Norms	Theory of Planned Behavior (Ajzen, 2012); UTAUT (Venkatesh et al., 2003)	Wang et al., 2017; Sanusi et al., 2024	H1a, H1b, H1c
Technologist Role	TPACK Framework (Koehler, Mishra, & Cain, 2013)	Zakaria & Hashim, 2024; Celik, 2023	H2a, H2b
Student Influence	Sociocultural Theory (Vygotsky, 1978)	Elahi Shirvan et al., 2021; Waluyo & Kusumastuti, 2024; Kim et al., 2022	H3a, H3b, H3c
Process Facilitator Role	TPACK Framework (Ning et al., 2024); Facilitative Pedagogy (Guggemos & Seufert, 2021)	Holstein et al., 2019; Boubker, 2024;	H4a, H4b
Compatibility	UTAUT (Venkatesh et al., 2003); Adoption Models (Chen, 2011)	Schlager & Fusco, 2003	H5a, H5b
Perceived Attitude	Technology Acceptance Models (TAM, UTAUT)	Yue et al., 2024; Kim et al., 2022	H6a
Competency Building	TPACK-aligned Professional Development (Holstein et al., 2019)	Holstein et al., 2019; Wulandari & Purnamaningwulan, 2024	H6b
Behavioral Intention	Technology Acceptance Models (TAM, UTAUT)	Venkatesh et al., 2003	H6a, H6b

2.7 Partial Least Squares Structural Equation Modeling (PLS-SEM) and Importance Performance Matrix Analysis (IPMA)

Partial Least Squares Structural Equation Modeling (PLS-SEM) serves as a robust variance-based technique for examining complex predictive relationships among latent constructs, particularly in contexts where theoretical frameworks are still emerging or data characteristics, such as non-normality, moderate sample sizes, and multicollinearity, limit the suitability of covariance-based SEM. Unlike covariance-based approaches that emphasize model fit and theoretical confirmation, PLS-SEM prioritizes prediction and variance explanation, making it especially valuable for exploratory studies in educational technology where behavioral variables are interrelated and multidimensional (Hair et al., 2019; Sarstedt et al., 2021). The method enables simultaneous estimation of measurement and structural models, allowing for comprehensive evaluation of indicator reliability, validity, and hypothesized causal paths within a single analytical process. Its flexibility and minimal distributional assumptions make it appropriate for this study's sample of 146 teachers. Moreover, PLS-SEM's use of bootstrapping enhances the accuracy of path significance testing, providing stable estimates even with smaller samples and thus strengthening the reliability and predictive validity of the proposed model (Hair & Alamer, 2022; Xie et al., 2025).

Importance–Performance Matrix Analysis (IPMA) offers an interpretive layer to PLS-SEM results, enhancing the practical value of structural findings. IPMA evaluates both the relative importance of each latent construct in predicting key outcomes and their actual performance levels, allowing for the identification of high-impact areas that may be underperforming and warrant focused intervention (Hair & Alamer, 2022). Such dual assessment is especially valuable in educational innovation research, where an exclusive focus on statistical significance may fail to capture critical gaps between intention and real-world implementation. Integrating PLS-SEM with IPMA enables a richer understanding of both the theoretical and applied aspects of AI adoption in EFL education, bridging empirical results with actionable recommendations for professional development and policy improvement (Ting et al., 2020; Xie et al., 2025). Employing these complementary methods ensures that research conclusions are not only statistically sound but also relevant to pedagogical and institutional practice.

3 Method

3.1 Research design

A survey-based approach was used to investigate the perceptions and utilization of AI (artificial intelligence) by EFL (English as a foreign language) teachers. The PLS-SEM (Partial Least Squares Structural Equation Modeling) technique was applied to analyze the complex relationships between the observed and unobserved variables of the study (Hair et al., 2014). This method was chosen because it is suitable for small sample sizes, and its robustness allows for the treatment of the measurement model and structural model simultaneously (Sarstedt et al., 2021). Using the final PLS model, this study serves two purposes: first, to identify the many factors that influence EFL teachers' acceptance of AI and second, to determine how these factors influence their use of AI in the development of teaching modules.

3.2 Participants

The participants of this study included all 146 EFL teachers from senior high schools who participated in a two-day workshop on AI usage for language learning, conducted in the second week of June 2024. The workshop aimed to enhance teachers' competency in AI implementation for teaching strategies on the first day, and in creating teaching materials for receptive (listening and reading) and productive (speaking and writing) skills on the second day. The teachers came from six regencies and one municipality in Greater Solo, one of the metropolitan areas in Indonesia. As representatives of their schools, the teachers voluntarily attended the workshop, motivated by their eagerness to learn how to integrate AI into their EFL teaching. The participants, comprising all workshop attendees, met the recommended minimum sample size for PLS-SEM as suggested by Wong (2019). They were predominantly teaching at public schools and their educational backgrounds were at the undergraduate level, with a substantial number having over 16 years of working experience. Moreover, most participants used Android phones as their daily driver, highlighting the varied and technologically engaged context within which the study was conducted. Table 2 presents the more detailed demographic data of the participants.

Table 2
Participants' Demography

Gender	**Frequency**	**Percent**
Female	105	71.9
Male	41	28.1
School Origin		
Private	37	25.3
Public	109	74.7
Education		
Graduate	27	18.5
Undergraduate	119	81.5
Working Experience		
> 16 Years	92	63
1-5 Years	20	13.7
11-15 Years	23	15.8
6-10 Years	11	7.5
Daily Driver		
Android	136	93.2
iPhone	10	6.8

3.3 Research instruments

The instruments used in this study were adapted from Breiki et al. (2023) for measuring subjective norms (5 items), compatibility (5 items), and perceived attitude (5 items); Huang et al. (2021) for assessing behavioral intention (5 items) and student influence (5 items); and Alamelu et al. (2022) for evaluating competency building (5 items), technologist (5 items), and process facilitator (5 items). The validity of these instruments was ensured through expert review by two professors with over 25 years of experience in English education and linguistics. They provided feedback to enhance readability, clarity, and accuracy. Pilot testing was conducted with 30 potential respondents before the workshop, confirming reliability and validity with a Cronbach's Alpha value of 0.813 and R-values ranging from 0.388 to 0.428 against an R-table value of 0.296, ensuring the robustness of the measurement tools (Brown, 2022).

3.4 Data collection

This research employed a total sampling approach, targeting all senior high school EFL teachers who participated in a structured professional development workshop across six regencies and one municipality in [Anonymized]. The total sampling method was intentionally selected to maximize representativeness and ensure comprehensive coverage of the target population, significantly reducing sampling bias and enhancing the generalizability of the findings (Creswell & Creswell, 2017). Prior to data collection, ethical clearance was meticulously obtained from both the university's research ethics committee and the provincial education authority (Clearance No. 194.2/LPPM27.22/PT.01.03/2024). Ethical approval procedures followed established guidelines, including clear communication of research objectives, confidentiality guarantees, participant rights, and the voluntary nature of participation, adhering strictly to ethical standards for educational research (American Educational Research Association, 2011). Participants provided informed consent electronically before commencing the questionnaire, thereby ensuring transparent and ethical compliance throughout the data collection process.

Data were collected immediately after the workshop via an online Google Forms questionnaire, an approach chosen to leverage the immediacy and efficiency of digital data collection platforms (Dörnyei & Taguchi, 2009). The timing of questionnaire administration was strategically designed to capture the most authentic and accurate reflections of teachers' immediate post-training perceptions and behavioral intentions toward AI integration in their instructional practices. This timing decision is crucial in educational research, as immediate post-intervention assessment reduces recall bias and enhances data reliability (Fraenkel et al., 2018). Furthermore, real-time monitoring and follow-up reminders were employed to guarantee completeness and accuracy of responses. Rigorous data quality checks included screening for completeness, absence of duplicate entries, and balanced geographic distribution of responses across participating regions, thus enhancing the dataset's representativeness and robustness (Hair et al., 2019). These comprehensive procedural safeguards contributed significantly to the overall integrity, validity, and credibility of the research findings.

Table 3 below clearly summarizes each stage of the research procedures, emphasizing key activities, ethical considerations, and justifications for methodological choices, providing a transparent overview of the entire data collection process.

Table 3

Key Activities, Ethical Considerations, and Justifications for Methodological Choices

Stage	**Activity/Process**	**Ethical/Procedural Consideration**	**Methodological Justification/Reference**
Sampling	Total sampling of all senior high school EFL teachers attending the AI workshop	Reducing sampling bias, enhancing representativeness	Creswell & Creswell (2017)
Ethical Approval	Ethical clearance from the university and provincial education office	Adherence to ethical guidelines; informed consent	AERA (2011)
Questionnaire Administration	Immediate post-workshop using Google Forms	Capturing authentic immediate perceptions; reducing recall bias	Dörnyei & Taguchi (2009)
Participant Monitoring	Real-time monitoring, reminders, and follow-ups to ensure response completeness	Ensuring data accuracy and completeness	Fraenkel et al. (2018)
Data Quality Checks	Screening for missing data, duplicate responses, and balanced regional participation	Ensuring representativeness and data integrity	Hair et al. (2019)

3.5 Data analysis

Data analysis employed Partial Least Squares Structural Equation Modeling (PLS-SEM) using SmartPLS 4 (Hair & Alamer, 2022; Ringle et al., 2022), selected for its suitability in handling small samples, non-normal data, and complex models with multiple latent constructs. The method facilitates simultaneous testing of measurement and structural models, making it ideal for exploratory studies focused on explaining variance rather than confirming established theories (Hair et al., 2019; Sarstedt et al., 2021). Prior to analysis, data were screened for missing values, duplicate entries, and uneven regional representation to ensure integrity and accuracy. Following established PLS-SEM procedures, analysis proceeded in two stages. The first stage, the measurement model assessment, evaluated the reliability and validity of the constructs. Indicator loadings were examined to confirm item relevance, while internal consistency was verified through Cronbach's alpha and composite reliability. Convergent validity was assessed using Average Variance Extracted (AVE), and discriminant validity was confirmed through the Heterotrait–Monotrait (HTMT) ratio, ensuring that each construct measured a distinct theoretical dimension (Hair et al., 2019).

The second stage, structural model assessment, tested the hypothesized relationships among constructs. Multicollinearity was examined using Variance Inflation Factors (VIF) to ensure the independence of predictors. Path significance was determined through bootstrapping with 5,000 resamples, generating stable estimates for t-statistics and p-values. Model strength and predictive accuracy were further assessed using R^2, Q^2, and f^2 values, indicating the explanatory power and effect sizes of each construct (Hair & Alamer, 2022). To deepen interpretation and highlight practical implications, Importance–Performance Matrix Analysis (IPMA) was applied as a complementary diagnostic tool. IPMA ranks constructs based on both their importance (total effects on the target construct) and performance (mean latent variable scores), revealing areas where improvement would yield the most impact (Hair & Alamer, 2022; Ting et al., 2020). Results identified "compatibility" as a construct with high importance but moderate performance, indicating a need for targeted professional development to enhance AI integration among EFL teachers. Combining statistical rigor with practical insights ensures that findings are both analytically robust and pedagogically meaningful (Hair et al., 2019).

4 Findings

The study employed Partial Least Squares Structural Equation Modeling (PLS-SEM) to explore the interrelationships among constructs influencing EFL teachers' adoption of AI in language education. The analysis proceeded in two main stages. First, the measurement model was assessed to evaluate the reliability and validity of the constructs. This stage involved examining the strength of item loadings, internal consistency reliability, and both convergent and discriminant validity. Second, the structural model was tested to examine hypothesized relationships, assess multicollinearity, and determine the model's explanatory power using path coefficients, effect sizes, and predictive relevance indices. Finally, Importance-Performance Matrix Analysis (IPMA) was conducted to identify key constructs that warrant strategic attention due to their combined high importance and low performance.

4.1 Measurement model assessment

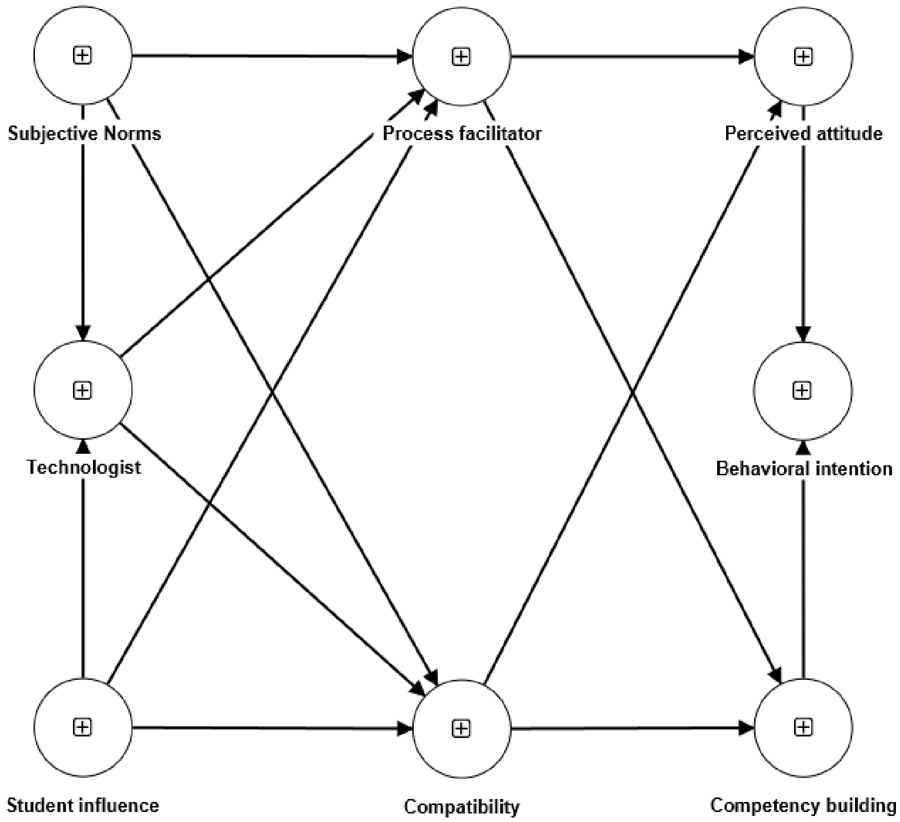
4.1.1 Indicator loading, internal consistency reliability, and convergent validity value

The structural model presented in Figure 2 illustrates the relationships between various constructs in the context of EFL teachers' perceptions and use of AI in language education. The model comprises both endogenous and exogenous constructs. The exogenous constructs in the model include Subjective

Norm and Student Influence, while the endogenous constructs are Technologist, Process Facilitator, Compatibility, Competency Building, Perceived Attitude, and Behavioral Intention.

Figure 1

Model Specification



These relationships are visually represented with arrows which indicate the direction of influence, providing a comprehensive view of how subjective norms, student influence, and technological proficiency contribute to the overall integration of AI tools in EFL teaching. The model aims to shed light on the pathways through which these factors interact and ultimately influence teachers' behavioral intentions to use AI in their teaching practices.

The indicator loadings (see Table 4) for the reflective measurement model were assessed, and values above 0.70 were considered satisfactory as they indicate that the construct can explain more than 50% of the indicator's variance (Sarstedt et al., 2021). Table 2 illustrates that the outer loadings ranged from 0.654 to 0.937, demonstrating satisfactory reliability for most indicators. However, a few indicators, such as CB_4 with a loading of 0.654, did not meet the recommended threshold. This item was retained as it had no influence to improve the model fit as suggested by Wong (2019). Indicator loadings between 0.4 and 0.7 are acceptable under certain conditions. According to Hair et al. (2017, 2019), such indicators should only be removed if their exclusion notably improves the composite reliability above 0.7. Additionally, values in this range are justifiable if other measures, like convergent validity (AVE) and internal consistency reliability (e.g., Cronbach's alpha and composite reliability), meet acceptable thresholds.

In addition, Internal consistency reliability was evaluated using Cronbach's alpha (α) and Composite Reliability (CR), with acceptable thresholds being greater than 0.70 (Hair et al., 2019). The results showed that all constructs had α and CR values exceeding 0.70, confirming high reliability (Table 2). Convergent validity was measured by the Average Variance Extracted (AVE), which should be above 0.50 (Hair et al., 2019). All constructs achieved AVE values above the threshold, ranging from 0.622 to 0.818, indicating good convergent validity.

Table 4

Indicator loading, Internal Consistency Reliability, and Convergent Validity Value

Construct	Outer Loadings	α	CR	AVE
BI_1	0.937	0.944	0.944	0.818
BI_2	0.911			
BI_3	0.909			
BI_4	0.904			
BI_5	0.860			
CB_1	0.776	0.902	0.906	0.718
CB_2	0.846			
CB_3	0.853			
CB_4	0.654			
CB_5	0.848			
C_1	0.879	0.858	0.884	0.638
C_2	0.868			
C_3	0.857			
C_4	0.830			
C_5	0.800			
PA_1	0.840	0.878	0.885	0.733
PA_2	0.828			
PA_3	0.862			
PA_4	0.893			
PF_1	0.763	0.848	0.852	0.622
PF_2	0.769			
PF_3	0.747			
PF_4	0.830			
PF_5	0.830			
SI_1	0.856	0.904	0.909	0.777
SI_2	0.844			
SI_3	0.916			
SI_5	0.907			
SN_1	0.781	0.870	0.879	0.659
SN_2	0.746			
SN_3	0.799			
SN_4	0.877			
SN_5	0.849			
T_1	0.861	0.845	0.852	0.763
T_2	0.880			
T_3	0.879			

Remark: Behavioral intention (BI), Compatibility (C), Competency building (CB), Perceived attitude (PA), Process facilitator (PF), Student influence (SI), Subjective Norms (SN), Technologist (T)

4.1.2 Discriminant Validity (DV)

To confirm that each construct captured a distinct theoretical concept, discriminant validity was examined using the Heterotrait-Monotrait (HTMT) ratio. All HTMT values ranged from 0.556 to 0.879, remaining well below the conservative threshold of 0.90 (Hair et al. 2019). This confirms that the constructs were not only internally consistent but also empirically distinct from one another, thereby reducing the risk of conceptual overlap in the model.

4.2 Structural model assessment

4.2.1 Multicollinearity testing

Before interpreting the structural model, it was necessary to confirm that the independent variables were not excessively correlated. Multicollinearity was assessed using the Variance Inflation Factor (VIF), with all values falling below the commonly accepted cutoff of 3.0 (Hair et al. 2019). The highest observed VIF was 2.649, associated with Student Influence. These results ensure that collinearity is not a threat to the validity of the regression coefficients and affirm the stability of parameter estimates across the model.

4.2.2 Hypotheses testing

The hypotheses were tested using the PLS-SEM algorithm and bootstrapping techniques. The hypotheses testing section explores the relationships between variables in the proposed model. The results, summarized in Figure 2, reveal that most hypothesized relationships were supported according the recommended threshold of t statistics value ≥ 1.96 (Hair et al. 2019). Based on path analysis results in Table 3, the hypothesis H1a, which postulates that Subjective Norms positively influence Process Facilitator, was supported ($\beta = 0.301$, $p = 0.015$). This indicates that the expectations and norms within the educational community significantly shape EFL teachers' views on using AI for material development. In contrast, hypothesis H1b, which suggests that Subjective Norms influence Technologist, was not supported ($\beta = 0.175$, $p = 0.061$). This finding may reflect the moderate digital literacy among teachers, where community expectations do not necessarily translate to perceived technological proficiency. Hypothesis H1c, asserting that Subjective Norms impact Compatibility, was strongly supported ($\beta = 0.394$, $p < 0.001$). This underscores the role of community norms in enhancing teachers' perception of AI tools fitting well with their teaching methods. Additionally, hypotheses H2a and H2b, which propose that Technologist influences both Compatibility ($\beta = 0.332$, $p < 0.001$) and Process Facilitator ($\beta = 0.220$, $p = 0.038$), were supported. This suggests that teachers who are more technologically proficient perceive AI tools as compatible with their teaching practices and effective in facilitating the teaching process.

In addition, hypotheses H3a, H3b, and H3c examine the impact of Student Influence on various constructs. Hypothesis H3a, which posits that Student Influence affects Technologist, was supported ($\beta = 0.609$, $p < 0.001$), highlighting that students' readiness and use of technology significantly enhance teachers' technological proficiency. This aligns with findings that integrating technology in classrooms can enhance students' learning experiences. Hypothesis H3b, which suggests Student Influence impacts Compatibility, was also supported ($\beta = 0.288$, $p < 0.001$), indicating that student engagement with technology positively influences teachers' perception of AI compatibility with teaching. Hypothesis H3c, proposing that Student Influence affects Process Facilitator, was supported ($\beta = 0.288$, $p = 0.028$), showing that student interactions with technology enhance teachers' view of AI as a helpful teaching facilitator. Hypotheses H4a and H4b, which explore the effects of Process Facilitator on Competency Building ($\beta = 0.396$, $p < 0.001$) and Perceived Attitude ($\beta = 0.115$, $p = 0.099$), yielded mixed results. While Process Facilitator significantly impacts Competency Building, its effect on Perceived Attitude was not significant, suggesting that while AI tools facilitate teaching processes, their influence on overall attitudes towards AI might require further investigation. Table 5 presents the path analysis results.

Figure 2
Final Model

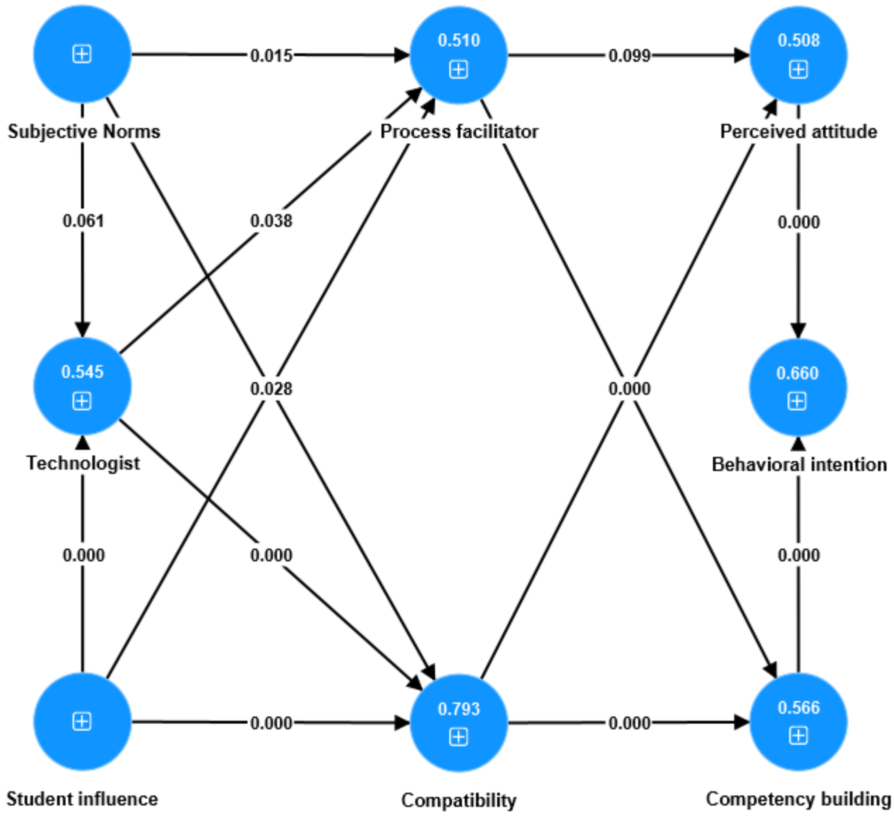


Table 5
Path Analysis Result

Hypotheses	Path	β	Mean	SD	T Statistics	P Values	Significance
H1a	Subjective Norms -> Process facilitator	0.301	0.297	0.124	2.425	0.015	Supported
H1b	Subjective Norms -> Technologist	0.175	0.173	0.094	1.870	0.061	Rejected
H1c	Subjective Norms -> Compatibility	0.394	0.395	0.064	6.120	0.000	Supported
H2a	Technologist -> Compatibility	0.332	0.329	0.059	5.580	0.000	Supported
H2b	Technologist -> Process facilitator	0.220	0.224	0.106	2.080	0.038	Supported
H3a	Student influence -> Technologist	0.609	0.613	0.094	6.452	0.000	Supported
H3b	Student influence -> Compatibility	0.288	0.292	0.076	3.790	0.000	Supported
H3c	Student influence -> Process facilitator	0.288	0.297	0.131	2.195	0.028	Supported
H4a	Process facilitator -> Competency building	0.396	0.414	0.098	4.042	0.000	Supported

H4b	Process facilitator -> Perceived attitude	0.115	0.119	0.069	1.650	0.099	Rejected
H5a	Compatibility -> Competency building	0.436	0.422	0.106	4.096	0.000	Supported
H5b	Compatibility -> Perceived attitude	0.634	0.632	0.068	9.304	0.000	Supported
H6a	Perceived attitude -> Behavioral intention	0.490	0.489	0.074	6.601	0.000	Supported
H6b	Competency building -> Behavioral intention	0.446	0.448	0.077	5.751	0.000	Supported

Moreover, the final set of hypotheses focuses on the relationships between Compatibility, Perceived Attitude, Competency Building, and Behavioral Intention. Hypotheses H5a and H5b, which posit that Compatibility influences Competency Building ($\beta = 0.436$, $p < 0.001$) and Perceived Attitude ($\beta = 0.634$, $p < 0.001$), were both supported. This indicates that when teachers perceive AI tools as compatible with their teaching practices, it significantly enhances their competency development and attitudes toward AI. Hypothesis H6a, suggesting that Perceived Attitude affects Behavioral Intention, was supported ($\beta = 0.490$, $p < 0.001$), highlighting that positive attitudes towards AI strongly predict teachers' intentions to use these tools. Finally, hypothesis H6b, proposing that Competency Building influences Behavioral Intention, was supported ($\beta = 0.446$, $p < 0.001$). This underscores that developing competencies in using AI tools is crucial for fostering teachers' intentions to integrate these technologies into their teaching practices. These findings collectively underscore the importance of aligning AI tools with teachers' existing practices and competencies to enhance their adoption and effective use in the classroom.

4.2.3 Coefficient of determination (R^2), Effect size (f^2), and Predictive relevance (Q^2)

The coefficient of determination (R^2) values indicates the predictive power of the model. We follow R^2 criteria (0.75: substantial, 0.50: moderate, and 0.25: weak) suggested by Hair et al. (2019). As shown in Table 4, the R^2 values for Behavioral Intention (0.660), Compatibility (0.793), Competency Building (0.566), Perceived Attitude (0.508), Process Facilitator (0.510), and Technologist (0.545) suggest that the model has strong predictive accuracy. The obtained R^2 values demonstrate that our model possesses moderate to substantial predictive power across key constructs, confirming its strong overall predictive accuracy and validating its effectiveness in this context, as shown in Table 6.

Table 6

Coefficient Determination (R^2)

Construct	R Square	R Square Adjusted	Consideration
Behavioral intention	0.660	0.655	Strong
Compatibility	0.793	0.788	Strong
Competency building	0.566	0.560	Strong
Perceived attitude	0.508	0.501	Strong
Process facilitator	0.510	0.499	Strong
Technologist	0.545	0.538	Strong

Effect sizes (f^2) were calculated to assess the impact of each predictor on the endogenous constructs follow the criteria of 0.02 (small), 0.15 (medium), and 0.35 (large) as suggested by Hair et al. (2019). The effect sizes ranged from very small (e.g., Subjective Norms -> Perceived Attitude, f^2 = 0.016) to large (e.g., Compatibility -> Perceived Attitude, f^2 = 0.485), indicating varying degrees of influence among the predictors (Table 5). The range of effect sizes from very small to large indicates that while certain predictors like Compatibility significantly influence the endogenous constructs, others such as Subjective Norms have minimal impact, emphasizing the varying degrees of importance among predictors within the model, as presented in Tables 7 and 8.

Table 7

Effect Size (f^2)

Path	f2	Effect size
Subjective Norms -> Process facilitator	0.097	Small
Subjective Norms -> Technologist	0.037	Small
Subjective Norms -> Compatibility	0.393	Large
Technologist -> Compatibility	0.241	Medium
Technologist -> Process facilitator	0.045	Small
Student influence -> Technologist	0.444	Large
Student influence -> Compatibility	0.151	Medium
Student influence -> Process facilitator	0.064	Small
Process facilitator -> Competency building	0.214	Medium
Process facilitator -> Perceived attitude	0.016	Very Small
Compatibility -> Competency building	0.26	Medium
Compatibility -> Perceived attitude	0.485	Large
Perceived attitude -> Behavioral intention	0.525	Large
Competency building -> Behavioral intention	0.434	Large

Table 8

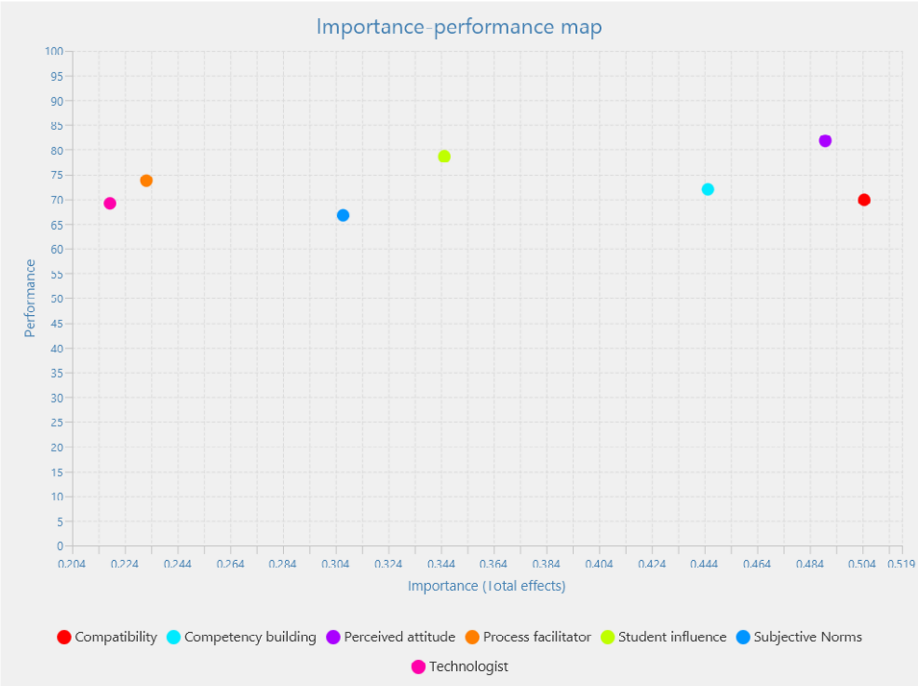
Predictive Relevance (Q^2)

	SSO	SSE	Q^2 (=1-SSE/SSO)
Behavioral intention	730	340.814	0.533
Compatibility	730	321.068	0.560
Competency building	730	478.157	0.345
Perceived attitude	584	371.414	0.364
Process facilitator	730	511.34	0.300
Student influence	584	584	0.000
Subjective Norms	730	730	0.000
Technologist	438	262.527	0.401

4.3 Importance-Performance Matrix Analysis (IPMA)

Figure 3

IPMA Map



The Importance-Performance Matrix Analysis (IPMA) provides a comprehensive view of the constructs' importance and performance (Ting et al., 2020), offering actionable insights for enhancing the integration of AI tools in EFL teaching. The IPMA results, as depicted in Table 9 and Figure 3, allow us to prioritize areas for improvement by mapping constructs into four quadrants: "Keep Up the Good Work," "Concentrate Here," "Low Priority," and "Possible Overkill." The IPMA results highlight key areas for strategic improvement. Focusing on Compatibility, which is both highly important and underperforming, could significantly enhance the integration of AI tools in EFL teaching. Maintaining high performance in areas like Perceived Attitude and Competency Building is essential, while optimizing resources in less critical areas ensures efficient use of efforts and resources. This balanced approach will support the successful adoption and utilization of AI tools, ultimately enriching the educational experiences of EFL teachers and their students.

Table 9

IPMA Results

	Importance	**Performance**
Compatibility	0.505	69.830
Competency building	0.446	71.985
Perceived attitude	0.490	81.830
Process facilitator	0.232	73.797
Student influence	0.345	78.611
Subjective Norms	0.307	66.728
Technologist	0.219	69.157

5 Discussions and Implications

This study aimed to comprehensively explore the factors influencing Indonesian EFL school teachers' behavioral intentions toward AI adoption following a professional development workshop that featured practical exposure to ChatGPT. By addressing notable gaps in previous literature, this research integrated multiple influential constructs, encompassing subjective norms, technologist roles, student influence, process facilitation, compatibility, perceived attitudes, and competency building, within a holistic theoretical model grounded in both the Unified Theory of Acceptance and Use of Technology (UTAUT; Williams et al., 2015; Venkatesh et al., 2003) and Diffusion of Innovations (DOI) theory (García-Avilés, 2020). Notably, prior studies predominantly assessed singular or isolated factors (Teng, 2024; Seo et al., 2024), thus neglecting the intricate interactions among constructs in shaping teachers' sustained adoption of technological innovations post-training. Furthermore, this research explicitly included the roles of subjective norms and student influences, factors frequently overlooked despite their crucial implications for long-term pedagogical transformations (Ebneyamini & Sadeghi Moghadam, 2018; Waluyo & Kusumastuti, 2024).

The methodological choice of Partial Least Squares Structural Equation Modeling (PLS-SEM) proved particularly valuable in this study, as it enabled a simultaneous assessment of the measurement and structural models, capturing both direct and indirect relationships among the seven latent constructs. This approach strengthened the study's analytical precision by accommodating the relatively small sample size and non-normal data distribution typical of teacher survey research, while still offering robust estimation of path coefficients and mediating effects (Hair et al., 2019; Hair & Alamer, 2022; Sarstedt et al., 2021). The model's ability to reveal interconnections among subjective norms, technologist roles, student influence, and compatibility provided deeper insights into the mechanisms through which post-training behavioral intentions toward AI adoption are formed. Moreover, the integration of PLS-SEM with Importance–Performance Matrix Analysis (IPMA) extended these findings beyond statistical confirmation, translating them into actionable recommendations for professional development and policy design (Hair & Alamer, 2022; Ting et al., 2020). Thus, the use of PLS-SEM not only validated the theoretical integration of UTAUT and DOI frameworks but also enhanced the practical relevance of the study's outcomes for sustainable AI adoption in EFL education.

The findings provide robust evidence supporting the critical yet complex role of subjective norms. Specifically, subjective norms positively influenced the process facilitator role (H1a) and compatibility (H1c), reinforcing the assertion that institutional encouragement significantly fosters teachers' receptivity toward integrating innovative technologies (Ebneyamini & Sadeghi Moghadam, 2018; Wang et al., 2017). In contrast, subjective norms exhibited no statistically significant influence on teachers' technological identities (H1b), emphasizing the reality that while institutional pressure may catalyze initial experimentation, it alone is insufficient to cultivate deep technological proficiency or technological identity (Sanusi et al., 2024). This finding notably diverges from general expectations within UTAUT models, which typically associate strong social influence with widespread adoption (Venkatesh et al., 2003). Such divergence highlights the necessity of accompanying institutional support with targeted, ongoing professional development to ensure sustainable teacher adoption and identity formation as proficient technologists.

Technologist roles significantly impacted teachers' perceived compatibility with AI (H2a) and their efficacy as process facilitators (H2b). These findings resonate strongly with prior research indicating that enhanced technological pedagogical content knowledge (TPACK) is essential for successfully embedding new technologies into existing instructional routines (Koehler et al., 2013; Zakaria & Hashim, 2024). Furthermore, the present study expands the theoretical scope by empirically validating student influence as a pivotal determinant influencing technologist roles (H3a), compatibility perceptions (H3b), and facilitation effectiveness (H3c). This aligns with sociocultural frameworks emphasizing reciprocal teacher-student dynamics in technology integration (Elahi Shirvan et al., 2019; Kim et al., 2022; Vygotsky, 1978). Particularly, the strong influence of students confirms Waluyo and Kusumastuti's (2024) argument that students' digital enthusiasm significantly shapes teachers' technological identities and instructional practices, positioning students as active stakeholders rather than passive recipients.

Regarding process facilitation, the results provide mixed yet insightful evidence. While the process facilitator role positively influenced competency building (H4a), aligning with studies emphasizing the effectiveness of facilitative pedagogies for competency development (Guggemos & Seufert, 2021; Holstein et al., 2019), it did not significantly affect perceived attitudes toward AI (H4b). This discrepancy highlights potential complexities between practical skill acquisition and attitudinal changes toward technology, suggesting that teachers may develop competencies without necessarily cultivating positive attitudes. Such findings stress the need for deeper exploration into emotional and psychological factors influencing technological acceptance, as suggested by recent discussions of technological anxiety and age-related adoption barriers (Teng, 2024; Kim et al., 2023).

Finally, compatibility emerged as a critical and influential construct, significantly enhancing both competency building (H5a) and perceived attitudes toward AI (H5b), ultimately influencing behavioral intentions through competency (H6b) and perceived attitudes (H6a). These outcomes affirm prior theoretical propositions that compatibility is fundamental for reducing integration barriers, boosting perceived utility, and promoting sustainable technological adoption (Chen, 2011; Schlager & Fusco, 2003; Venkatesh et al., 2003; Waluyo & Isma, 2025). The Importance-Performance Matrix Analysis (IPMA) further reinforced compatibility as a strategic priority due to its high impact yet moderate performance levels. This finding resonates with Hair and Alamer (2022) and Yue et al. (2024), who assert that enhancing alignment between technological tools and existing pedagogical practices is critical for successful long-term integration. All these insights advocate for targeted professional development interventions focused explicitly on compatibility, alongside fostering positive teacher attitudes and comprehensive competency development. By advancing a multidimensional understanding of these interrelationships, this study significantly contributes to both theoretical knowledge and practical implementation strategies for the sustained and effective integration of AI in EFL education contexts.

6 Conclusion

6.1 Summary of the findings

This study found that multiple interconnected factors, encompassing subjective norms, technological competence, student influence, process facilitation, and compatibility, shape Indonesian EFL teachers' perceptions and behavioral intentions toward adopting AI after professional development. Subjective norms positively influenced teachers' roles as process facilitators and their perceptions of AI compatibility, but did not significantly foster technological competence, underscoring the limits of social influence without targeted skill development. Technological proficiency and student influence were key drivers of AI integration, with student engagement enhancing teachers' willingness to adopt AI tools. Compatibility between AI applications and existing pedagogical practices emerged as a pivotal enabler, significantly boosting both competencies and positive attitudes toward AI. These relationships were further contextualized within Indonesia's collectivist culture, where personal intentions are balanced with community expectations.

6.2. Limitations of the study

The study's scope was limited to EFL teachers in Indonesian senior high schools who participated in a single, two-day workshop, which may restrict the generalizability of the findings to other educational contexts, subjects, or regions. Data collection relied on self-reported perceptions immediately after training, which may be influenced by short-term enthusiasm and social desirability bias. The cross-sectional design limits the ability to capture changes in perceptions or behavioral intentions over time. Additionally, while the study integrated multiple constructs within a robust PLS-SEM and IPMA framework, it did not examine external factors such as long-term institutional policy changes, resource allocation, or longitudinal teaching outcomes.

6.3 Recommendations for future research

Future research should adopt longitudinal designs to track whether post-training intentions translate into sustained AI use and improved learning outcomes over time. Expanding the participant pool to include teachers from different subject areas, school levels, and geographic regions would enhance the external validity of the findings. Mixed-methods approaches, incorporating classroom observations and interviews, could provide richer insights into the contextual and behavioral dynamics of AI adoption. Further studies should also investigate the role of institutional policy, leadership support, and ongoing professional learning communities in strengthening both the compatibility of AI tools with pedagogy and the development of teachers' technological identities.

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Lastika Ary Prihandoko is a senior lecturer at Universitas Sebelas Maret. His research interests include academic writing, partial least squares structural equation modeling (PLS-SEM), and EFL education. He has received various research grants from the Indonesian government since 2020.

Suci Nugrah Amalia holds a doctoral degree in English Language Education. She earned her master’s degree from Universitas Sebelas Maret, Indonesia, and her doctorate from Universitas Negeri Malang, Indonesia. She received scholarships from the Indonesia Endowment Fund for Education (LPDP) to support both her master’s and doctoral studies. Her research interests include English Language Teaching (ELT), willingness to communicate, and teacher professional development.

Priyatno Ardi is an Associate Professor of Applied English Linguistics in the English Language Education Study Program at Universitas Sanata Dharma, Indonesia. His research interests include learner autonomy, student engagement, technology in language learning, EFL teacher education, and applied linguistics.

Budi Waluyo, listed among the World’s Top 2% Scientists (Stanford 2025), serves at the Research Center for Language Teaching and Learning, Walailak University (THA). He earned degrees from the University of Bengkulu (IDN, BA, Indonesian Ministry of Education Scholarship), the University of Manchester (UK, MA, Ford Foundation International Fellowships Program), and Lehigh University (USA, PhD, Fulbright Presidential Scholarship), and was a research fellow at Columbia University (USA). A Fellow of the UK Higher Education Academy (FHEA), he has over 10 years of English teaching experience in higher education. His 72 Scopus-indexed publications (H-index: 18) are internationally recognized in English language teaching, educational technology, and international education.