Available online at www.ijournalse.org

Emerging Science Journal

(ISSN: 2610-9182)

Vol. 10, No. 3, June, 2026

Modelling Pre-Service English Teachers' Readiness for AI Integration: A TPACK–TAM Mixed-Methods Study

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Abstract

Artificial Intelligence (AI), particularly large language models such as ChatGPT, has advanced rapidly recently, revolutionizing English Language Teaching (ELT); nonetheless, its pedagogically meaningful integration remains uneven and contingent on teacher preparation. Emerging research indicates that AI adoption is shaped more by teachers' professional knowledge and acceptance views than by technological hurdles. However, empirical information on their interaction, particularly in underexplored contexts, remains scarce. Using an integrated Technological Pedagogical Content Knowledge (TPACK) and Technology Acceptance Model (TAM) framework, this study investigates pre-service English teachers' preparedness for AI integration, conceptualizing readiness as competence-informed acceptance, a novel construct that differs from traditional readiness frameworks by emphasizing the cognitive professional interplay between knowledge and beliefs rather than mere willingness or attitude. An explanatory sequential mixed-methods single-case design was utilized, with survey data ($n = 78$) analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) and qualitative responses examined through reflexive thematic analysis. The results demonstrated that pedagogical knowledge was the strongest predictor of reported usefulness ($\beta = 0.607$, $p < 0.001$) and perceived ease of use ($\beta = 0.546$, $p < 0.001$). Prior AI experience directly predicted intention ($\beta = 0.208$, $p < 0.001$) and moderated the usefulness–intention link ($\beta = 0.061$, $p = .044$), although perceived ease of use had a greater impact on planned future use ($\beta = 0.299$, $p < 0.001$) than perceived usefulness ($\beta = 0.192$, $p = 0.003$). The qualitative results identified the importance of pedagogical rationale and context limitations. The research contributes to the theory, as it combines TPACK and TAM and offers context-related evidence in the MENA region, which supports the preparation of AI in ELT with pedagogy as a priority. Qualitative findings highlighted the role of pedagogical reasoning and contextual constraints. The study advances theory by integrating TPACK and TAM, demonstrating that professional knowledge operates indirectly through acceptance beliefs, and provides context-sensitive evidence from the Middle East and North Africa (MENA) region, supporting pedagogy-first AI preparation in ELT.

Keywords:

Artificial Intelligence in Education;

Teacher Readiness;

TPACK;

Technology Acceptance Model (TAM);

Pedagogical Knowledge;

Mixed-Methods Research.

Article History:

Received:	08	February	2026
Revised:	17	May	2026
Accepted:	20	May	2026
Published:	01	June	2026

1- Introduction

Automated writing evaluation systems, intelligent tutoring systems, and large language models (LLMs) like ChatGPT are forms of Artificial Intelligence (AI) technologies that are becoming more integrated into the educational process. Scholars have identified some of the benefits of AI use in the field of English Language Teaching (ELT) to include personalization of instruction, increasing learner autonomy, and instant feedback; research has shown that AI can have positive effects on engagement, feedback quality, and assessment [1]. Despite such affordances, the pedagogically significant use of AI is uneven and contextual. Contrary to early assumptions that technological access is the primary barrier, recent studies indicate that teacher readiness, specifically the professional capacity to evaluate, adapt, and integrate AI tools, constitutes the major obstacle to successful AI implementation [2, 3]. AI can support instruction and

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DOI: https://doi.org/10.28991/ESJ-2026-010-03-020

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decrease the workload, but on the other hand, it brings up the issues of misinformation, academic dishonesty, reliance, creativity, and ethical accountability [4, 5]. The role of the teachers in this regard is, therefore, a critical mediator in the use of AI that promotes or disrupts learning.

The application of AI tools in a meaningful way needs specialized professional knowledge to assess outputs, create pedagogically suitable tasks, and match technology to the standards of the curricula. Competence is more conceptualized through the lens of Technological Pedagogical Content Knowledge (TPACK), and recent studies claim that AI-informed TPACK should be viewed as one of the keys to responsible integration [6, 7]. When there is no inbuilt knowledge, the implementation of AI will be shallow or pedagogically unsafe. Pre-service teachers' AI-TPACK positively predicted their perceived usefulness and ease of use of AI, which in turn shaped both their intention and actual usage of AI in teacher training contexts, directly extending the TAM framework to incorporate AI-specific professional knowledge as an antecedent of acceptance [8].

Studies based on TPACK demonstrate a disjointed preparedness in teachers; despite the presence of great technological knowledge, the intersection of technology, pedagogy, and content has not been developed in terms of pedagogical integration [9, 10]. The studies of English teachers emphasize technological pedagogical knowledge as one of the most significant predictors of AI readiness, but it is not actively incorporated into the system of teacher education [3]. The same gaps exist at all the levels of education, especially in ethical consciousness and content-sensitive application [11, 12]. Technology acceptance studies also show that professional knowledge is not a guarantee of the use of AI; TAM determines perceived usefulness (PU), perceived ease of use (PEOU), self-efficacy, and trust as the key factors of adoption intention [13, 14]. Recent findings suggest that TPACK and TAM are mutually reinforcing because professional knowledge can be used in shaping the perception of usefulness and manageability, which affects behavioral intention [2, 15]. Nevertheless, most studies analyzed these constructs individually, which restricts the knowledge on how competence is converted to readiness. Extending TAM beyond its traditional constructs, Şimşek et al. [16] found that metacognitive self-regulation and learning motivation exerted stronger effects on perceived usefulness and ease of use than external social influences among pre-service teachers, suggesting that intrinsic cognitive factors are primary drivers of generative AI acceptance in teacher education contexts.

These are problems that are especially applicable to pre-service teachers; most pre-service English teachers are positive about AI, but at the same time, they are also concerned with the accuracy, ethics, learners' dependency, and classroom control [17, 18]**.** Even though it is possible that training AI competence in the short run could improve pedagogical judgement in real-life settings, this approach should not be sufficient [19]. In the EFL context specifically, Harakchiyska [20] found that the actual learning of AI and demonstrated competence in delivering AI-supported lessons were the strongest predictors of pre-service English teachers' behavioral disposition to integrate AI in their L2 classrooms, with self-efficacy serving as a significant mediating mechanism—underscoring the insufficiency of mere attitudinal readiness without grounded AI competence. My intention is multidimensional, and affective variables, including AI anxiety and self-efficacy, also impact it in addition to professional knowledge [21, 15], meaning that readiness is not only one-dimensional.

The gaps in context also restrict the existing knowledge; most of the empirical studies have concentrated on technologically sophisticated areas; little has been done regarding the Middle East and North Africa (MENA). The Middle East and North Africa (MENA) region, including Oman, remains empirically underexplored in AI–ELT research despite national digital transformation agendas such as Oman Vision 2040 [22]. Existing studies have predominantly focused on technologically advanced Western and East Asian contexts [2, 3], leaving a contextual gap regarding how AI readiness manifests in settings where teacher education programs have yet to systematically embed AI pedagogy. The region has national policies focused on digital transformation and human capital development, such as the Oman Vision 2040. Global employability incorporates English education; even though it has been emphasized, the technological adoption of the ELT process remains disproportionate in Oman, and little empirical evidence can be found about the readiness of AI in the instructional environment. Moreover, the conceptualization of AI among the pre-service English teachers in Oman is not well known, nor is their willingness to use AI in pedagogy or how the professional knowledge is related to the beliefs in acceptance and future application.

In the absence of context-sensitive evidence, teacher education will be reduced to generic AI training models, which are out of sync with local realities. The multidimensionality of AI readiness as a construct is further demonstrated by Özüdoğru & Durak [23], whose PLS-SEM analysis of 816 pre-service teachers revealed that AI readiness encompasses cognitive, visionary, and ethical dimensions and is meaningfully differentiated by gender—underscoring the need for context-sensitive and differentiated frameworks rather than monolithic readiness models in teacher preparation. Similarly, Filiz et al. [24] found that K-12 teachers valued AI tools such as ChatGPT for their efficiency and adaptability but identified significant barriers including curriculum misalignment, ethical concerns, and cultural limitations in adapting AI-generated content to local instructional contexts—reinforcing the argument that successful AI integration is fundamentally a pedagogical and contextual challenge rather than a technological one.

To fill these theoretical and regional gaps, the current research will combine TPACK and TAM to theorize the construct of readiness through competence-informed acceptance, whereby perceptions of usefulness and easy access to such perceptions due to professional knowledge affect intention. It offers empirical data on the under-researched Omani setting regionally. The study applies the exploratory mixed-methods case study approach to determine the interaction between professional knowledge, acceptance beliefs, experience, and contextual factors to influence the readiness to adopt pedagogically sound and ethical AI integration. The aims of the research are to:

- Determine the impact of TPACK domains on acceptance beliefs.
- Identify predictors of AI intended use, and
- Determine the role of pedagogical rationale and situational limitations in defining readiness.

2- Conceptual Framework

In this study, readiness to incorporate AI is conceptualized as competence-based acceptance, meaning that teacher intentions are determined by the engagement between professional knowledge and technology acceptance beliefs; hence, readiness is viewed as a cognitive-professional process as opposed to mere willingness to use technology. The framework combines the TPACK model with TAM, with professional knowledge being an antecedent of acceptance beliefs. The integration of AI in ELT needs a meeting point of content, pedagogical and technological knowledge [25]; this relates to disciplinary knowledge to assess AI-generated products, pedagogical expertise to design and govern AI-mediated activities, and technological literacy to use AI-mediated tools responsibly, conceptualized as AI-informed TPACK [2]. The integration of TPACK and TAM in this study is justified by their theoretical complementarity: TPACK identifies the professional knowledge domains necessary for pedagogically sound technology use, while TAM specifies the belief-based mechanism through which such knowledge translates into intention. Readiness as "competence-informed acceptance" thus posits that professional knowledge does not directly determine intention; rather, it operates through the formation of perceived usefulness and ease of use, which serve as proximal cognitive mediators.

TAM explains how knowledge translates into intention through perceived usefulness (PU) and perceived ease of use (PEOU**)** [26]. Teachers' evaluations depend on instructional value and implementation effort, with acceptance beliefs mediating the competence–intention relationship. The composite framework hypothesizes TPACK domains as the antecedents of TAM constructs: more advanced pedagogical and technological knowledge leads to perceived complexity, increasing PEOU [14]; high-quality content knowledge leads to increased perceived value, increasing PU PEOU [27]. The usefulness appraisals and the intention are reinforced by prior AI experience [28, 29]. Overall, the TPACK-TAM framework describes the concept of AI readiness as a mediated process based on knowledge that determines future adoption in ELT.

Figure 1 shows the flowchart of the research methodology through which the objectives of this study were achieved.

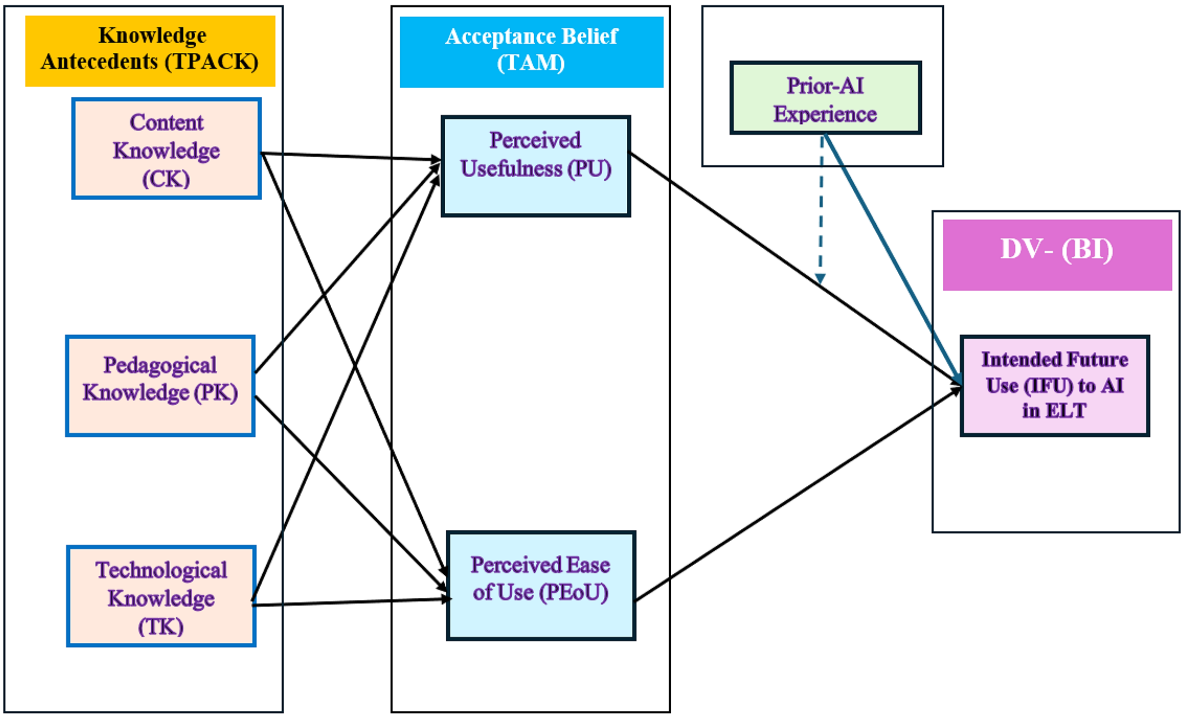

Figure 1. The Integrated TPACK–TAM Conceptual Framework for AI Adoption in ELT

3- Literature Review and Hypothesis Development

3-1- AI Integration in ELT and the Role of Teacher Knowledge

The available literature on the introduction of AI in ELT suggests that teacher knowledge is the key that defines meaningful use of AI. Empirical research indicates that AI-informed TPACK is a powerful predictor of readiness, behavioral intention, and classroom adoption, which outweighs traditional predictors of adoption, such as performance expectancy and social influence [2, 3]. The interventions of professional development also increase the competence and self-efficacy of AI, which validates preparedness as a capacity to develop [7]. According to qualitative and conceptual research, AI does not deprive teachers of their work to reform their role as pedagogical designers, deciders, and moral guardians, but it transforms them [6, 30, 31].

It is also referred to as a two-sided tool that offers educational assistance but also presents risks associated with fake data, academic dishonesty, and lack of creativity, which justifies the need to mediate AI by teachers [4, 5]**.** AI-TPACK is also brought to the fore in systematic reviews to create responsible learning environments [32, 33]. Even though ethical competence remains inadequate, current literature highlights the importance of AI literacy, ethical preparation, and affective mediation as a significant part of teacher knowledge [34]. According to learner research, the teacher support facilitates communication, emotional management, enjoyment, and well-being [35-37]. Although AI can enhance results, it will only be beneficial when pedagogical supervision is good enough because the lack of mediation can worsen limitations and learner anxiety [21, 38, 39]. Overall, the realization of the effective AI application in ELT is premised on teacher expertise, not technology alone.

3-2- Professional Knowledge and Acceptance Beliefs

In the TAM, the perceptions of the usefulness of AI (perceived usefulness (PU)) represent the perceptions of the instructional usefulness of AI, and the perceptions of the perceived ease of use (PEOU) represent the anticipated effort, complexity, and the ability to control [26]. In the case of pre-service teachers, such acceptance beliefs are embryonic and highly influenced by their emerging professional knowledge base, as it is conceptualized in the TPACK framework. As empirically validated, professional knowledge is never a direct translator to adoption intention; in fact, it affects them through the impact of PU and PEOU as central cognitive beliefs [27]. Investigations integrating TAM and TPACK demonstrate that content, pedagogical, and technological competences systematically shape how teachers evaluate the pedagogical value and usability of emerging technologies, including AI [2, 40]. Across these studies, a recurring methodological limitation emerges: most investigations analyze TPACK and TAM constructs separately, precluding empirical testing of the indirect effects of professional knowledge on intention through acceptance beliefs. Furthermore, findings regarding the moderating role of prior AI experience remain inconclusive, with some studies reporting significant amplification of the usefulness–intention link [14] and others finding no moderation [29]. These inconsistencies underscore the need for integrated modeling that simultaneously tests direct, indirect, and moderated pathways.

Content Knowledge (CK) allows teachers to evaluate the linguistic correctness and the available curriculum of AI-generated output and enhances PU and reduces uncertainty in usage [2, 14]. Pedagogical Knowledge (PK) enhances PU and reduces perceived instructional burden and improves PEOU by helping teachers visualize the ways of applying AI in instruction [27, 15]. In cases of generative AI where there are uncertainty and perceived risk, the influence of TK on PEOU is notably strong due to the reduction of the operational ambiguity and technology-related anxiety [14, 21, 40]. Accordingly, this study is proposed as follows:

H1a: *Content Knowledge (CK) is positively associated with Perceived Usefulness (PU) of AI tools for ELT.*

H1b: *CK is positively associated with Perceived Ease of Use (PEOU) of AI tools for ELT.*

H2a: *Pedagogical Knowledge (PK) is positively associated with Perceived Usefulness (PU) of AI tools for ELT.*

H2b: *PK is positively associated with PEOU of AI tools for ELT.*

H3a: *Technological Knowledge (TK) is positively associated with PU of AI tools for ELT.*

H3b: *TK is positively associated with PEOU of AI tools for ELT.*

3-3- Acceptance Beliefs and Intended Future Use of AI

TAM recognizes PU and PEOU as the closest variables to intention to adopt new technologies [26]. In the case of teacher education, these perceptions become especially salient since, in this case, pre-service teachers have little classroom experience and are more sensitive to instructional risk. As a result, the intentions towards the future are oriented mostly on the values of AI as something pedagogically valuable and practically possible to be implemented. Throughout the field of AI and educational technology studies, PEOU is a direct and indirect motivator of intention and often supports PU by decreasing perceived complexity and operational ambiguity [41, 42]. Similar processes can be noted in the case of AI-mediated informal language learning since protracted experience with generative systems can support grounded usefulness perceptions and consolidated intention [35]. Teacher-oriented studies also find PU to be among the strongest predictors of intention, with ease perceptions working mostly based on usefulness perceptions [2, 43]. Previous pre-service teacher populations also indicate the central position of PEOU in the initial adoption [44, 45].

Accordingly, the following hypotheses are proposed:

H4: *PU is positively associated with Intended Future Use (IFU) of AI tools for ELT.*

H5: *PEOU is positively associated with IFU of AI tools for ELT.*

H6: *PEOU is positively associated with PU of AI tools for ELT.*

3-4- Indirect Effects of Professional Knowledge through Acceptance Beliefs

The results of combined TAM-TPACK studies offer the fact that professional knowledge exerts the strongest influence on adoption intention due to PU and PEOU and not by direct effect [40, 46, 21]. Studies on generative AI indicate that the intention is supported by AI literacy and intelligent TPACK in the situations where the perceived usability and instructional value are elevated [2, 14]. In addition to competence, high-quality enactment involves mediation because of the contribution of evaluative beliefs and pedagogical orientations [47-49].

Accordingly, the following hypotheses are proposed:

H7a: *PU mediates the relationship between CK and IFU.*

H7b: *PEOU mediates the relationship between CK and IFU.*

H8a: *PU mediates the relationship between PK and IFU.*

H8b: *PEOU mediates the relationship between PK and IFU.*

H9a: *PU mediates the relationship between TK and IFU.*

H9b: *PEOU mediates the relationship between TK and IFU.*

3-5- The Role of Prior AI Experience

The experience in using AI tools is assumed to enhance the perceived intention to use it further since the individual will be less inclined to experience doubts and base the assessment on practice [35, 50]. Even though studies on moderation are inconclusive [29, 38]**,** more recent studies indicate that experience may enhance the PU-IFU relationship by transforming abstract usefulness perceptions into judgments supported by confidence [22]. Prior AI experience (AIEX) has a dual role in this model; on the one hand, it is an independent predictor of intention, and on the other hand, it enhances the relationship between perceived usefulness and intention to use in the future.

Overall, the preceding hypotheses establish professional knowledge as an antecedent to acceptance beliefs and acceptance beliefs as predictors of intention. However, the translation of perceived usefulness into intended future use may depend on an additional individual-difference factor: prior direct experience with AI tools. Experience provides a grounded basis for evaluating usefulness, potentially strengthening the belief–intention relationship. Accordingly, the following hypotheses are proposed:

H10: *Prior experience with AI tools (AIEX) is positively associated with IFU.*

H11: *AIEX positively moderates the relationship between PU and IFU.*

4- Methodology

The paper will follow a theory-based exploratory approach to analysis by exploring the willingness of pre-service English language teachers to adopt AI in ELT. With the combined TPACK-TAM framework, readiness is conceptualized as competence-informed acceptance, where professional knowledge influences the acceptance beliefs and intended use; the goal is to produce context-sensitive explanatory knowledge as opposed to confirmatory generalization.

4-1- Research Design

This study adopted an explanatory sequential mixed-methods design [51] within a bounded case study [52]. This technique permits the evaluation of links between professional expertise, acceptance beliefs, prior AI experience, and Intended Future Use (IFU), alongside participants situated pedagogical reasoning. The study had two related parts; first, a structured survey examined TPACK dimensions, Perceived Usefulness (PU), Perceived Ease of Use (PEOU), prior AI experience, and IFU. Second, open-ended questions explored pedagogical affordances and constraints, ethical concerns, and instructional reasoning. Integration occurred at the interpretation stage using established mixed-methods strategies

[53], with a "following a thread" approach linking quantitative patterns to qualitative explanations [54]. The case was bounded by a single institution and cohort, enabling focused contextual analysis. The explanatory sequential design was selected over alternative mixed methods approaches because the primary research aim was to explain quantitative relationships, specifically, how professional knowledge influences intention through acceptance beliefs, rather than to converge data types (convergent design) or explore a phenomenon qualitatively before measurement (exploratory design). This design allows qualitative data to function as an explanatory follow-up, illuminating the reasoning processes underlying statistical patterns.

4-2- Context and Participants

The research was carried out at A'Sharqiyah University, Oman, on the English Language track of the Diploma in Educational Qualification course in the College of Arts and Humanities. The graduates of this one-year post-bachelor program (33 credit hours) are ready to teach due to the theoretical studies and the practicum. Although the broad area of educational technology is covered, specific AI pedagogy remains underdeveloped, and this setting is appropriate to consider formative AI preparedness. Data were collected in the academic year 2025-2026.

The strategy adopted was a census sampling, which requested all the enrolled pre-service teachers to respond voluntarily and in an anonymous manner; the overall number of valid responses was 78, and this number is suitable for analysis using the Partial Least Squares Structural Equation Modeling (PLS-SEM) of exploratory models [55]**.** The participants were mostly women, had bachelor's degrees in the fields related to English, and had little formal training in AI. This limited sample from a single institution inevitably affects generalizability; findings are contextually bound and require replication across diverse Omani and MENA institutions before broader claims can be made. The single-case design prioritizes depth and theoretical coherence over statistical representativeness.

4-3- Instrument Development and Validation

An English online questionnaire was used for the data collection. Items were adapted, validated instruments and contextualized to AI-supported ELT (Appendix I). In the case of parsimony, TPACK was modeled into three domains, such as Content Knowledge (CK), Pedagogical Knowledge (PK), and Technological Knowledge (TK), all of which included five items based on Schmidt et al. [56] and Chai et al. [57]. PU and PEOU (five items each) were based on Davis [26] and Venkatesh & Davis [58], and IFU (five items) was based on Venkatesh et al. [59]. All closed-ended items used five-point Likert scales. The qualitative aspect comprised five open-ended questions related to the experiences with AI, perceived affordances and constraints, instructional uses, and ethical issues. The extent of content validity was determined based on the opinion of three experts, yielding a scale-level Content Validity Index of 0.91. A pilot study with 15 comparable participants demonstrated strong reliability (Cronbach's $\alpha > 0.80$). Cognitive debriefing ensured that there were clarity and an average time of 15 minutes, and some slight refinements were made. Items were adapted from validated instruments: Content Knowledge (CK), Pedagogical Knowledge (PK), and Technological Knowledge (TK) from Schmidt et al. [56] and Chai et al. [57]; Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) from Davis [26]; Intended Future Use (IFU) from Venkatesh et al. [59]. All closed-ended items used five-point Likert scales.

Data were collected via an online questionnaire in English. Items were adapted from validated instruments and contextualized to AI-supported ELT (Appendix I). For parsimony, TPACK was operationalized into three domains: Content Knowledge (CK), Pedagogical Knowledge (PK), and Technological Knowledge (TK), each comprising five items adapted from Schmidt et al. [56] and Chai et al. [57]. PU and PEOU (five items each) were adapted from Davis [26] and Venkatesh & Davis [58]**,** while IFU (five items) was adapted from Venkatesh et al. [59]. All closed-ended items used five-point Likert scales.

The qualitative part contained five open-ended questions inquiring about the experiences of AI, the perceived affordances and limitations, the use of AI in instruction, and the issue of ethics. Expert validation was done by three scholars who have a scale-based Content Validity Index of 0.91. A pilot study of 15 similar participants revealed good reliability (Cronbach $\alpha > 0.80$). Cognitive debriefing ensured that the clarity and average time of completion of 15 minutes were achieved with a few refinements.

The qualitative component included five open-ended questions addressing AI experiences, perceived affordances and constraints, instructional uses, and ethical concerns. Content validity was established through expert review by three specialists, yielding a scale-level Content Validity Index of 0.91. A pilot study with 15 comparable participants demonstrated strong reliability (Cronbach's $\alpha > 0.80$). Cognitive debriefing confirmed clarity and an average completion time of 15 minutes, with some minor refinements.

4-4- Data Collection Procedures

A'Sharqiyah University's Research Ethics Committee provided the ethical approval, with institutional permission secured from the college administration. Participants were recruited via an official email distributed by a program administrator, including an information sheet and a link to the anonymous questionnaire. Informed consent was obtained electronically. Data were collected over three weeks in 2026, with two reminder emails sent to enhance response rates.

4-5- Data Analysis

SPSS (v.28) and SmartPLS 4 were used for the quantitative data analysis following established PLS-SEM procedures; the analysis included i) preliminary screening (descriptive statistics, normality assessment, and common method bias using Harman's single-factor test); ii) measurement model evaluation (Composite Reliability > 0.70; AVE > 0.50; indicator loadings > 0.708; HTMT < 0.90); and iii) structural model assessment (VIF < 5; bootstrapping for hypothesis testing; and explanatory and predictive evaluation using R^2, Q^2, and f^2). Qualitative data were analyzed using reflexive thematic analysis [60] through iterative familiarization, coding, theme development, and refinement. While inductive in approach, analysis was theoretically informed by the integrated TPACK–TAM framework.

4-6- Ethical Considerations and Methodological Rigor

The response was voluntary and anonymous, and no personally identifiable information was gathered. The data was safeguarded in institutional servers that were encrypted with passwords. To ensure rigor, the study opted for validated instruments, transparent SEM reporting, and adherence to qualitative trustworthiness criteria of credibility, dependability, transferability, and confirmability [61].

5- Results

5-1- Assessment of the Measurement (Outer) Model

Seven reflective constructs were considered in the measurement model: Content Knowledge, Pedagogical Knowledge, Technological Knowledge, Perceived Usefulness, Perceived Ease of Use, Prior AI Experience, and Intended Future Use (see Figure 2). As recommended by the best practices in variance-based SEM, construct reliability, convergent validity, and discriminant validity were evaluated using various criteria to guarantee internal consistency and construct distinctiveness before the hypothesis testing [62, 63].

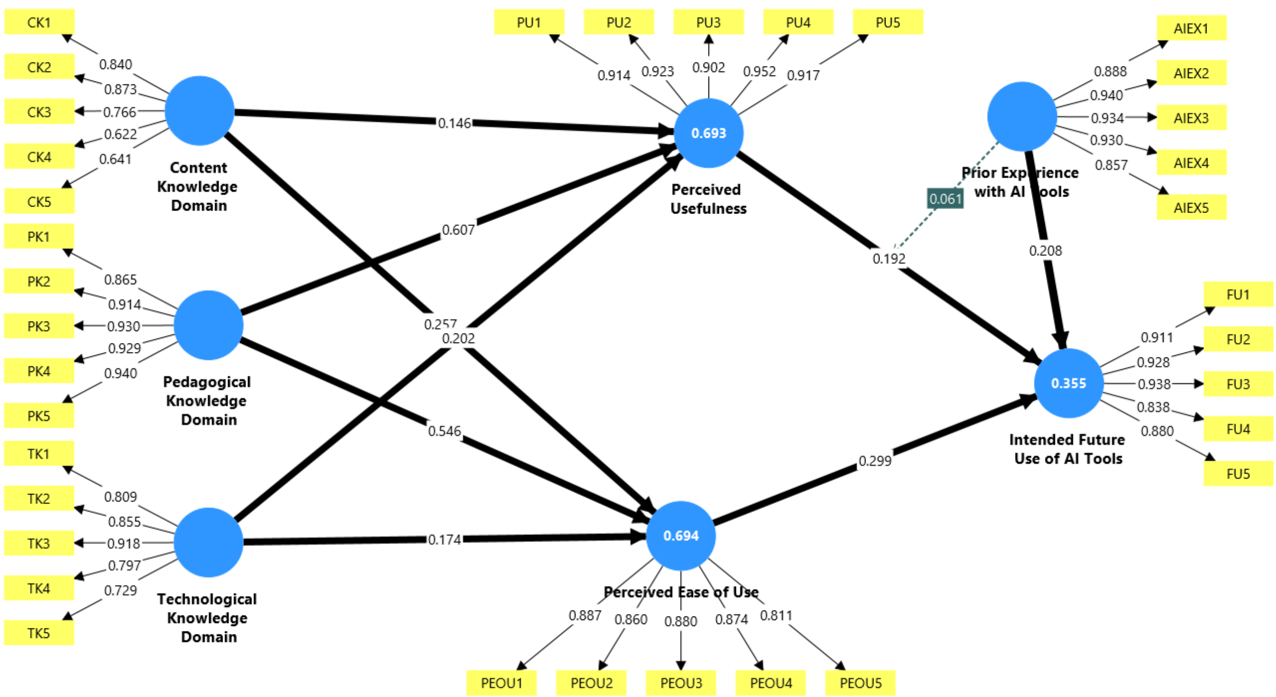

Figure 2. Outer Model Assessment

5-1-1- Reliability and Convergent Validity

The Cronbach's alpha and composite reliability (CR) were used to evaluate construct reliability. Table 1 reveals that all constructs were > 0.70, which is the recommended level of internal consistency [61]. Cronbach alpha values were between 0.810 and 0.956, and CR was between 0.834 and 0.957, suggesting the models' reliability. Standardized indicator loading was used to assess convergent validity and average variance extracted (AVE). After the iterative refinement, all the retained indicators had loadings ≥ 0.50, and most were greater than 0.70. Indicators with a value range of 0.50-0.70 were kept in the model if their elimination did not enhance CR or AVE, and their inclusion is theoretically justified [61]. Table 1 indicates a higher AVE value (0.571 up to 0.850) than the recommended value of 0.50, which confirms that each construct explained over 50% of the variance of its indicators.

Table 1. Reliability and Convergent Validity Metrics

Construct	Item	Factor Loadings	Cronbach's Alpha	Composite Reliability (CR)	Average Variance Extracted (AVE)
Prior Experience with AI Tools	AIEX1	0.888	0.948	0.953	0.829
	AIEX2	0.940			
	AIEX3	0.934			
	AIEX4	0.930			
	AIEX5	0.857			
Content Knowledge Domain	CK1	0.840	0.810	0.834	0.571
	CK2	0.873			
	CK3	0.766			
	CK4	0.622			
	CK5	0.641			
Intended Future Use of AI Tools	FU1	0.911	0.941	0.957	0.810
	FU2	0.928			
	FU3	0.938			
	FU4	0.838			
	FU5	0.880			
Perceived Ease of Use	PEOU1	0.887	0.914	0.915	0.745
	PEOU2	0.860			
	PEOU3	0.880			
	PEOU4	0.874			
	PEOU5	0.811			
Pedagogical Knowledge Domain	PK1	0.865	0.952	0.954	0.839
	PK2	0.914			
	PK3	0.930			
	PK4	0.929			
	PK5	0.940			
Perceived Usefulness	PU1	0.914	0.956	0.957	0.850
	PU2	0.923			
	PU3	0.902			
	PU4	0.952			
	PU5	0.917			
Technological Knowledge Domain	TK1	0.809	0.880	0.888	0.678
	TK2	0.855			
	TK3	0.918			
	TK4	0.797			
	TK5	0.729			

Note. CR = composite reliability; AVE = average variance extracted.

5-1-2- Discriminant Validity

Discriminant validity was investigated to confirm that the latent constructs represent experimentally distinct concepts. Consistent with present SEM standards, discriminant validity was examined using three complementing approaches: the Fornell–Larcker criterion, the heterotrait–monotrait ratio (HTMT), and cross-loading analysis. Table 2 showed that the square root of the AVE for each construct (diagonal values) exceeded its correlations with all other constructs, which met the Fornell–Larcker criterion [64]; it indicates that each construct shares more variance with its own indicators than with other latent variables.

Table 2. Fornell–Larcker Discriminant Validity Assessment

Construct	CK	IFU	PK	PEOU	PU	AIEX	TK
Content Knowledge	**0.755**						
Intended Future Use of AI Tools	0.630	**0.900**					
Pedagogical Knowledge	0.567	0.527	**0.916**				
Perceived Ease of Use	0.629	0.550	0.791	**0.863**			
Perceived Usefulness	0.563	0.516	0.806	0.798	**0.922**		
Prior Experience with AI Tools	0.569	0.456	0.528	0.530	0.497	**0.910**	
Technological Knowledge	0.361	0.306	0.574	0.580	0.604	0.256	**0.824**

Note: Diagonal elements (bold) represent √AVE; off-diagonal elements denote inter-construct correlations.

To further reinforce the assessment, the HTMT ratios were computed; the values of all the HTMT were below 0.90, and the majority of them were below the more conservative value of 0.85, thus, supporting the idea of discriminant validity and overcoming the fear of common method bias [62, 65]; these findings are presented in Table 3.

Table 3. Heterotrait–Monotrait Ratio (HTMT)

Construct	CK	IFU	PK	PEOU	PU	AIEX	TK
Content Knowledge							
Intended Future Use of AI Tools	0.694						
Pedagogical Knowledge	0.611	0.548					
Perceived Ease of Use	0.698	0.581	0.842				
Perceived Usefulness	0.609	0.536	0.843	0.844			
Prior Experience with AI Tools	0.644	0.470	0.551	0.563	0.520		
Technological Knowledge	0.400	0.330	0.628	0.643	0.658	0.278	

As presented in Table 4, the cross-loadings demonstrated that each indicator loaded more strongly on its intended construct than on any other construct, further substantiating the measurement models' discriminant validity. These results collectively provide robust evidence of the conceptual and empirical distinctiveness of the constructs, thereby supporting the measurement models' adequacy.

Table 4. Cross-Loading Analysis

Construct	CK	IFU	PK	PEOU	PU	AIEX	TK
AIEX1	0.454	0.363	0.381	0.411	0.377	0.888	0.173
AIEX2	0.548	0.432	0.487	0.505	0.482	0.940	0.249
AIEX3	0.489	0.404	0.447	0.448	0.429	0.934	0.199
AIEX4	0.560	0.462	0.538	0.518	0.464	0.930	0.244
AIEX5	0.526	0.405	0.536	0.517	0.502	0.857	0.293
CK1	0.840	0.363	0.453	0.507	0.480	0.440	0.322
CK2	0.873	0.386	0.526	0.565	0.510	0.479	0.356
CK3	0.766	0.395	0.335	0.393	0.348	0.422	0.214
CK4	0.622	0.317	0.222	0.279	0.224	0.377	0.103
CK5	0.641	0.552	0.494	0.530	0.459	0.421	0.278
FU1	0.591	0.911	0.484	0.515	0.487	0.442	0.260
FU2	0.633	0.928	0.548	0.574	0.526	0.484	0.317
FU3	0.608	0.938	0.512	0.527	0.502	0.453	0.316
FU4	0.471	0.838	0.382	0.388	0.379	0.296	0.209
FU5	0.499	0.880	0.411	0.435	0.395	0.334	0.252
PEOU1	0.537	0.472	0.663	0.887	0.644	0.458	0.550
PEOU2	0.558	0.437	0.626	0.860	0.604	0.399	0.498
PEOU3	0.484	0.456	0.648	0.880	0.588	0.455	0.461
PEOU4	0.535	0.456	0.686	0.874	0.668	0.458	0.472
PEOU5	0.587	0.538	0.768	0.811	0.898	0.502	0.512

PK1	0.467	0.438	0.865	0.674	0.684	0.422	0.518
PK2	0.494	0.460	0.914	0.716	0.740	0.452	0.540
PK3	0.504	0.477	0.930	0.693	0.741	0.454	0.544
PK4	0.562	0.527	0.929	0.773	0.771	0.547	0.519
PK5	0.563	0.507	0.940	0.763	0.750	0.537	0.512
PU1	0.496	0.467	0.747	0.726	0.914	0.431	0.606
PU2	0.532	0.498	0.736	0.732	0.923	0.468	0.524
PU3	0.474	0.444	0.688	0.694	0.902	0.416	0.556
PU4	0.518	0.478	0.778	0.756	0.952	0.463	0.595
PU5	0.571	0.491	0.760	0.769	0.917	0.512	0.501
TK1	0.258	0.159	0.441	0.468	0.467	0.156	0.809
TK2	0.322	0.301	0.498	0.526	0.529	0.276	0.855
TK3	0.322	0.289	0.534	0.533	0.550	0.224	0.918
TK4	0.282	0.233	0.470	0.443	0.459	0.146	0.797
TK5	0.302	0.271	0.414	0.408	0.473	0.247	0.729

5-2- Structural Model Estimation

The structural model was analyzed using PLS-SEM in SmartPLS 4.0; consistent with the integrated TPACK–TAM framework, direct paths from Content, Pedagogical, and TK to IFU were omitted, as professional knowledge was theorized to influence intention indirectly through PU and PEOU; path coefficients and significance were estimated through bootstrapping with 5,000 resamples [61]. The model examined the effects of TPACK domains on acceptance beliefs, which predicted IFU, while prior AI experience was included as both a direct predictor and a moderator of the Perceived Usefulness–intention relationship. Figure 3 presents the structural model with bootstrapped estimates.

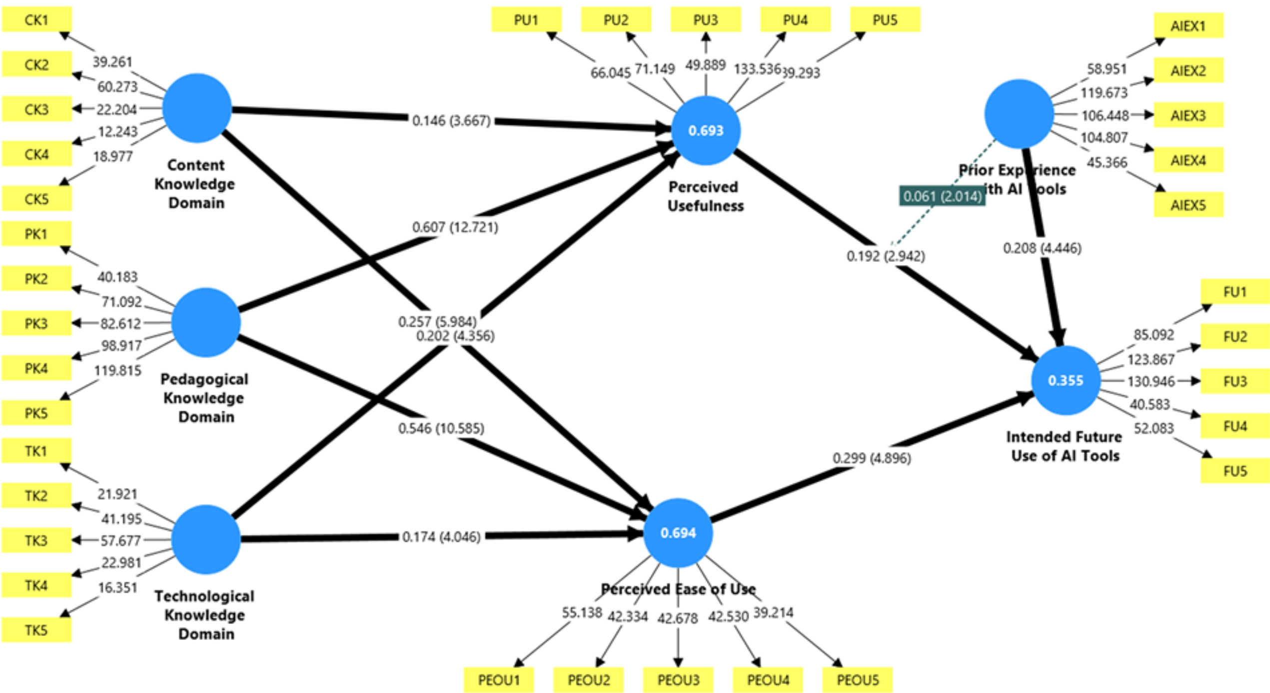

Figure 3. Structural Model with Bootstrapped Estimates

5-3- Hypothesis Testing: Direct Effects

The results of the structural model also lend a great deal of empirical evidence towards the hypothesized relationships. In line with H1a-H3b, all three knowledge areas of professionals were significant predictors of both beliefs. Of them, the influence of pedagogical knowledge (PK) had the most significant effects on PU (β = 0.607) and PEEU (β = 0.546), which highlights its pivotal role in the formation of AI-related assessments. The same was also found with content knowledge (CK) and technological knowledge (TK), which had significant, but more moderating, effects on both constructs of acceptance, but not dominating. The dominance of pedagogical knowledge in predicting both PU and PEOU (β = 0.607 and β = 0.546, respectively) underscores that, for pre-service teachers, AI acceptance is fundamentally shaped by how AI aligns with instructional practice rather than by technical competence alone. This pattern suggests that pedagogical knowledge functions as a cognitive schema through which AI tools are evaluated.

Based on TAM assumptions, acceptance beliefs were both significant predictors of intended future use (IFU). H4 and H5 were supported with the strongest impact of PEOU (β = 0.299) over PU (β = 0.192), which indicates the salience of perceived controllability and feasibility in pre-service teachers. Also, prior AI experience (AIEX) had a significant predictive value in IFU (β = 0.208), which supported H10 and showed that experience in terms of familiarity enhances adoption intentions beyond the evaluation based on beliefs (see Table 5).

Overall, the findings prove the suggested TPACK-TAM framework, showing that professional knowledge indirectly influences AI adoption intentions via acceptance beliefs, and pedagogical knowledge is the key mechanism behind competence-based acceptance.

Table 5. Structural Model Assessment (Direct Effects)

H	Structural Path	β	t	p	Decision
H1a	CK → PU	0.146	3.667	< 0.001	Supported
H1b	CK → PEOU	0.257	5.984	< 0.001	Supported
H2a	PK → PU	0.607	12.721	< 0.001	Supported
H2b	PK → PEOU	0.546	10.585	< 0.001	Supported
H3a	TK → PU	0.202	4.356	< 0.001	Supported
H3b	TK → PEOU	0.174	4.046	< 0.001	Supported
H4	PU → IFU	0.192	2.942	0.003	Supported
H5	PEOU → IFU	0.299	4.896	< 0.001	Supported
H10	AIEXP → IFU	0.208	4.446	< 0.001	Supported

Note. CK = Content Knowledge; PK = Pedagogical Knowledge; TK = Technological Knowledge; PU = Perceived Usefulness; PEOU = Perceived Ease of Use; IFU = Intended Future Use; AIEXP = Prior AI Experience.

5-4- *Mediation Analysis*

According to the mediation analysis, there is strong evidence supporting the competence-informed acceptance mechanism of the integrated TPACK-TAM framework. All hypothesized indirect paths (H7a-H9b) were all statistically significant, which proves that professional knowledge domains affect intended future use of AI tools (IFU) by the influence of acceptance beliefs and not by direct effects alone.

In content knowledge (CK), both the mediation through PEOU (β = 0.077) and PU (β = 0.028) were both significant; this implies that disciplinary expertise promotes adoption in large part by decreasing perceived complexity and uncertainty as opposed to increasing perceived instructional value only. In the same way, the mediated effect of pedagogical knowledge (PK) was the most significant in general, and it was most significant via PEOU (β = 0.163) and then PU (β = 0.116). These results support the key place of pedagogical competence in eliciting professional knowledge into practical adoption intentions (see Table 6).

In the case of technological knowledge (TK), both mediated predictors were also important, although with a relatively smaller value, meaning that technical competence serves as a predictor of intention through the promotion of the perception of usability and, to a smaller degree, the perception of usefulness. Collectively, the results confirm that PU and PEOU fully operationalize the pathway from professional knowledge to intention, providing strong empirical validation for readiness as competence-informed acceptance.

Table 6. Analysis of Indirect Effects

H	Indirect Structural Path	β	t	p	Decision
H7a	CK → PU → IFU	0.028	2.153	0.031	Supported
H7b	CK → PEOU → IFU	0.077	3.644	< 0.001	Supported
H8a	PK → PU → IFU	0.116	2.794	0.005	Supported
H8b	PK → PEOU → IFU	0.163	4.383	< 0.001	Supported
H9a	TK → PU → IFU	0.039	2.520	0.012	Supported
H9b	TK → PEOU → IFU	0.052	3.189	0.001	Supported

Note. CK = Content Knowledge; PK = Pedagogical Knowledge; TK = Technological Knowledge; PU = Perceived Usefulness; PEOU = Perceived Ease of Use; IFU = Intended Future Use.

5-5- Moderation Analysis: Prior Experience with AI Tools

The moderating effect of prior experience with AI tools was tested (see Table 7) to find out whether prior exposure preconditions the relationship between perceived usefulness and intended future use of AI tools. The interaction effect between prior experience with AI tools and perceived usefulness was significant (β = 0.061, p = .044). This finding shows that the positive correlation between perceived usefulness and future adoption intentions is supported by experience. Stated differently, the more practical experience the pre-service teachers have with the use of AI tools, the more their perceptions of usefulness are positively translated into the intentions to use the technologies. Although its interaction is rather small, the statistical significance of the effect indicates that experiential familiarity increases the motivational effect of usefulness beliefs. This finding highlights the need to expose teachers to AI tools early and continuously in teacher education programs because the experience seems to enhance the efficiency of cognitive assessments in influencing adoption intentions.

Table 7. Moderation Analysis (Prior Experience with AI Tools)

H	Interaction Path	β	t	p	Decision
H11	AIEXP × PU → IFU	0.061	2.014	0.044	Supported

5-6- Assessment of Explanatory Power, Predictive Relevance, and Effect Sizes

Effect sizes (f^2) were examined to assess the substantive contribution of predictors beyond statistical significance. Pedagogical Knowledge (PK) had a significant impact on Perceived Ease of Use ($f^2 = 0.51$) and Perceived Usefulness ($f^2 = 0.63$), which proved the centrality of this knowledge in the formation of the beliefs about acceptance and the importance of the pedagogy-based character of AI readiness in ELT. PK had a large effect on PU ($f^2 = 0.63$) and PEOU ($f^2 = 0.51$), confirming that pedagogical knowledge is not merely statistically significant but practically substantive in shaping acceptance beliefs.

Content Knowledge (CK) and Technological Knowledge (TK) showed medium effects on the acceptance beliefs. CK had medium results on Perceived Ease of Use ($f^2 = 0.16$) and Perceived Usefulness ($f^2 = 0.15$), which show that disciplinary expertise can help in uncertainty reduction and value judgments on AI usage. Equally, Perceived Ease of Use ($f^2 = 0.15$) and Perceived Usefulness ($f^2 = 0.17$) also had medium effects on TK, with technological competence being one of the facilitating conditions of usability perceptions and instructional assessment. Though less strong than PK, the medium effects of CK and TK imply that AI readiness is a complementary pattern of professional knowledge domains as opposed to pedagogy only.

For Intended Future Use, the effect sizes of Perceived Ease of Use ($f^2 = 0.047$) and prior AI experience were minor ($f^2 = 0.047$), whereas the effect of Perceived Usefulness was minimal ($f^2 = 0.019$), which suggests that there are many minor factors instead of one overwhelming influence on the intention to adopt AI. Pathways that were found to be not significant were seen as having no significant practical effect (see Table 8).

Table 8. Assessment of Explanatory Power (R^2), Predictive Relevance (Q^2predict), and Effect Sizes (f^2)

Endogenous Construct	R^2	Q^2predict	Predictor Path	f^2	Effect Size
Perceived Ease of Use (PEOU)	0.694	0.685	CK → PEOU	0.16	Medium
			PK → PEOU	0.51	Large
			TK → PEOU	0.15	Medium
Perceived Usefulness (PU)	0.693	0.684	CK → PU	0.15	Medium
			PK → PU	0.63	Large
			TK → PU	0.17	Medium
Intended Future Use (IFU)	0.355	0.359	PEOU → IFU	0.047	Small
			PU → IFU	0.019	Negligible
			AIEXP → IFU	0.047	Small

Note. Effect size thresholds follow Cohen (1988): 0.02 (small), 0.15 (medium), 0.35 (large).

5-7- Qualitative Results: Pre-Service Teachers' Perspectives on AI Integration in ELT

5-7-1- Overview of Qualitative Analysis

An open-ended questionnaire was used to collect qualitative data for the study, capturing participants' experiences, pedagogical reasoning, perceived affordances, and concerns regarding the use of AI in ELT. The responses were analyzed using reflexive thematic analysis following the six-phase process proposed by O'Cathain et al. [54]. This approach involved an iterative and inductive analysis guided by theory through the integrated TPACK-TAM framework. The analysis identified five interrelated themes that collectively describe pre-service teachers' conceptualizations of AI readiness, acceptance, and future pedagogical use. The qualitative findings are consistent with and complementary to the quantitative results, as they reveal the underlying reasoning processes that support perceived usefulness, perceived ease of use, and intentions for future use.

5-7-2- Pedagogical Value as the Primary Lens for Judging AI Usefulness

The participants consistently evaluated AI tools through their pedagogical contribution, rather than technological novelty; AI was perceived as useful when it aligned clearly with instructional goals, particularly in relation to feedback provision, language practice, and learner support. Respondents highlighted AI's capacity to provide immediate, individualized feedback, especially for writing and speaking tasks that are challenging to manage in large or time-constrained classrooms, and to generate practice activities, model responses, and explanatory scaffolds. Crucially, usefulness was framed as conditional rather than inherent. Participants emphasized that AI becomes pedagogically valuable only when guided by teacher intent and oversight. This conditional framing helps explain why pedagogical knowledge emerged as the strongest predictor of perceived usefulness in the quantitative model.

"AI is useful when it helps me achieve my lesson objectives, not just because it is advanced technology."

5-7-3-Ease of Use as Confidence-Dependent Rather Than Tool-Dependent

Enhancements in perceptions of ease of use were strongly associated with pedagogical confidence, previous exposure, and professional preparedness, as opposed to the technical complexity of AI tools. Those who already had some experience reported AI tools as easy to use and navigate, and those who had no experience expected to experience cognitive overload and confusion. Some of the respondents reported that even technically easy-to-use tools might seem challenging without an obvious pedagogical intent. The ease of use was thus positioned as a pedagogical knowledge feature as opposed to the interface design. This point of view can offer a qualitative explanation of the quantitative fact that pedagogical knowledge was more likely to predict perceived ease of use than technological knowledge.

"AI tools are easy only if you know why you are using them in your lesson."

5-7-4- Pedagogical Knowledge as the Bridge between AI and Classroom Practice

One of the most notable qualitative findings is that the participants perceived pedagogical knowledge as the primary tool that links AI tools to successful practice in the classroom. The respondents explained that they utilized their knowledge about learners, teaching techniques and evaluation principles to decide when, how and whether AI can be utilized. AI was mostly framed more as an aide concept and a supplementary tool, especially in practice, feedback, and differentiation, as opposed to a substitute for teacher teaching.

This agency view, with teachers as central, asserts the aspect of AI as a supportive device that is integrated into pedagogical decision-making. The theme qualitatively supports the direct and indirect high-level effects of pedagogical knowledge that were found in the structural model.

"AI should support my teaching decisions, not replace them."

5-7-5- Institutional and Ethical Constraints Shaping Adoption Readiness

Although the overall views on AI were generally positive, the respondents acknowledged contextual factors that reduced their intention to adopt AI. The most frequently mentioned obstacles were the lack of formal training on AI tools, the lack of guidance on how to use AI efficiently and preserve privacy, the fear of over-dependency on AI by the learners, and the lack of awareness of the policies and application in classrooms within the institution. The ethical factors were especially acute; the participants highlighted the role of teachers to promote fairness, transparency, and pedagogical integrity in the use of AI. These fears did not lead to the elimination of AI, but rather to the need to have a systematic approach and professional growth. This theme justifies why acceptance was not translated to blind and unquestioning zeal and underpins why the study focused on context-sensitive preparedness as opposed to technological determinism.

"Without clear training and rules, using AI in class can be risky."

5-7-6- Future-Oriented Teacher Identity and Conditional Adoption Intentions

Speaking of the future usage, the participants expressed conditional but positive plans to use AI in their professional practice. Most of them imagined themselves to be discriminating, discriminative and critical consumers as opposed to being automated or regular adopters. The role of AI in lesson preparation, feedback, and learner support was expected to increase, but teacher judgment and human interaction were always presented as the most important in effective ELT. Intended future use was therefore framed as situated and purposeful, rather than habitual or compulsory. This theme aligns with TAM assumptions regarding intention, whilst extending them by foregrounding the role of professional identity and pedagogical values in shaping adoption decisions.

"I will use AI when it improves learning, not just because it is available."

5-7-7- Integration with Quantitative Findings

The qualitative results elaborate and expand the quantitative results in three main aspects: to begin with, they explain why pedagogical knowledge had the greatest impact on perceived usefulness and perceived ease of use. Second, they show that the ease of use is based on the pedagogical confidence and technological competence alone. Third, they disclose that future use is contingent, influenced by moral aspects, institutionalized, and up-and-coming teacher identity. In general, the qualitative stage demonstrates that AI preparedness among pre-service English language teachers cannot be simply a technology acceptance process, but a pedagogically informed, situationally limited, and professionally mediated process.

6- Discussion

In this study, a theory-based description of the preparedness of pre-service English teachers to integrate Artificial Intelligence (AI) was created by the conceptualization of preparedness as competency-based acceptance achieved through the synthesis of TPACK and TAM. The results of the study through structural modeling and qualitative evidence reveal that the interaction of professional knowledge, acceptance beliefs, previous experience, and situational factors influences AI readiness in ELT.

6-1- Professional Knowledge as a Foundation for Acceptance Beliefs (RO1; H1–H3)

There is significant support for H1-H3 hypotheses, according to which Content Knowledge (CK), Pedagogical Knowledge (PK), and Technological Knowledge (TK) are significant to predict Perceived Usefulness (PU) and Perceived Ease of Use (PEOU), with Pedagogical Knowledge (PK) being the most effective predictor. This undermines the technologically oriented conceptualizations of AI competence by placing pedagogy at the center of acceptance, which is consistent with previous studies that have socially framed AI integration as a pedagogical, but not a technical, issue [2, 3]. This tendency is supported by the qualitative results, which show that the usefulness and ease of use were considered primarily in pedagogical aspects. The simplicity of the interface was less influential compared to the clarity of instructions, which is why PK was more influential than TK. CK favored judgments on linguistic correctness and curricular congruency, which strengthened the associations among leading instructional knowledge and trust [14], whereas TK led to a decrease in the uncertainty of operationalization [21]. Overall, these findings support the integrated framework by placing TPACK domains in the position of antecedents to acceptance beliefs.

6-2- Acceptance Beliefs as Predictors of Intended Future Use (RO2; H4–H6)

The results in support of H4-H6 affirm the fact that PU and PEOU are strong predictors of Intended Future Use (IFU), but PEOU has a stronger direct influence on the same than PU. This is indicative of the increased significance of feasibility and manageability among the pre-service teachers with little classroom experience, which aligns with other evidence of novice adoption patterns in the past [38, 39]. PU was also a major predictor, which aligns with the focus of TAM on the perceived value [2]. Qualitative information shows that usefulness was evaluated according to perceived, tangible pedagogical values as opposed to perceived technological advantage. The significant PEOU-PU relationship further supports the idea that the less complex, the better the perceived instruction value, and the relevance of TAM holds with the salience of ease perceptions in the pre-service environment. This finding aligns with An et al. [2], who reported pedagogical knowledge as the strongest TPACK predictor of AI acceptance among in-service English teachers but diverges from studies in STEM contexts where technological knowledge often exerts greater influence [15]. The divergence suggests domain specificity: in language teaching, pedagogy may assume heightened importance due to the inherently interactive and process-oriented nature of language instruction.

6-3- Acceptance Beliefs as Mediators between Knowledge and Intention (H7–H9)

The mediation analyses have strong support of H7-H9 and prove that CK, PK, and TK, in agreement with PU and PEOU, have complete effects on IFU. The highest indirect effects were observed with PK because it was proven to be the key to translating competence into motivation. CK worked primarily by eliminating uncertainty, whereas TK worked by increasing the intention through the perception of usability and perceived value. These results can be compared to the findings of extended TAM and TPACK studies that believe in the impact of professional knowledge on intention. These effects happen not directly but through the acceptance of beliefs [40, 27]. The qualitative evidence also demonstrates the mediation of this process by confidence and pedagogical reasoning, which empirically proves the readiness as competence-informed acceptance.

6-4- The Role of Prior AI Experience (RO2; H10–H11)

The fact that H10 and H11 are supported suggests that previous AI experience is a predictor of IFU and mediates between PU and IFU. Experience reduced uncertainty and increased perceived control [28], while strengthening the motivational impact of usefulness beliefs. Qualitative evidence indicates that experimentation helped participants to form realistic and responsible usage plans, which is consistent with the evidence that risk awareness aids in ethical adoption [24]. Despite its humble size, one can see the moderating effect, shedding light on the relevance of the early, systematic exposure to AI in the field of teacher education.

6-5- Readiness as a Pedagogically Mediated and Contextual Process (RO3)

The qualitative results revealed readiness as reflective, conditional, and influenced by pedagogical judgment, ethical issues, institutional restrictions, and training weakness. The participants considered AI as an extension of teacher expertise, not as an alternative, which supported teacher agency and their professional identities. These findings add to TAM because they introduce pedagogical reasoning and contextual considerations to the adoption processes. In general, the research results show that:

- The basic element of AI preparedness is pedagogical knowledge.
- Belief acceptance beliefs moderate the impact of professional knowledge.
- Ease of use is relevant, especially to pre-service teachers.
- Prior experience reinforces intention and belief-intention congruence.
- Readiness is context-specific and ethically mediated.

These contributions jointly contribute to the theoretical knowledge of AI preparedness in ELT and shape more practice-based AI preparation in teacher preparation.

6-6- Implications

6-6-1- Theoretical Implications

This research empirically validated an integrated TPACK-TAM model that conceptualizes readiness as competence-based acceptance, thereby contributing to the theory on AI integration in ELT. It shows that adoption intention is indirectly affected by professional knowledge through the adoption beliefs of perceived usefulness and perceived ease of use and elucidates an important mechanism that has been ignored in previous studies that have investigated knowledge and acceptance independently. The results also add value to the TPACK scholarship by demonstrating that pedagogical knowledge has a more powerful impact than technological knowledge on pre-service teachers to accept AI. This opposes technology-focused thinking and promotes the idea of AI integration as an inherently pedagogical activity, making AI-informed TPACK and helping to develop the reasoning of the instructions as foregrounding and ethical mediation. The study further expands TAM by showing the increased perceived ease of use salience in pre-service settings and evidence of the mediating capacity of prior AI experience in enhancing belief-intention relationships.

6-6-2- Practical Implications for Teacher Education

The high position of pedagogical knowledge implies that the training of AI is to be integrated into the course of study as a central part of pedagogy instead of being presented as a separate piece of technical training. The lesson design, feedback, differentiation, and assessment of AI tools should be modeled in programs to facilitate pedagogically based evaluation of AI tools. The mediating position of acceptance beliefs points to the necessity of facilitated experimentation, reflection, and critical evaluation to form realistic perceptions of usefulness and feasibility. The intention to adopt AI tools can be further reinforced by the initial, scaffolded exposure to AI tools with the assistance of explicit ethical guidelines. Lastly, institutional confusion in settings concerning ethical boundaries limited preparedness, which highlighted the necessity of consistent AI-use policies and integrated ethical literacy in teacher education.

6-6-3- Policy and Curriculum Implications

Digital transformation policies like the Oman Vision 2040 must address AI capacity-building based on pedagogy at the policy level instead of emphasizing the infrastructure. AI literacy, ethical reasoning, and pedagogical application should be integrated into the curriculum frameworks in terms of subject-specific teacher preparation and the alignment of AI competences with the professional teaching standards to ensure that policy aspirations are implemented and the gap between policy aspirations and classroom practice is bridged.

7- Conclusion

This research conceptualized AI readiness among pre-service English teachers as competence-informed acceptance, empirically validating an integrated TPACK–TAM framework in the under-researched Omani context. The findings demonstrate that professional knowledge “particularly pedagogical knowledge” does not directly determine AI adoption intention but instead operates through the mediating mechanisms of perceived usefulness and perceived ease of use. Pedagogical knowledge emerged as the strongest antecedent of both acceptance beliefs, highlighting that for pre-service teachers, AI readiness is fundamentally a pedagogical consideration rather than a technological one. Prior AI experience reinforced this process, directly predicting intention and moderating the usefulness–intention link, suggesting that early, scaffolded exposure to AI tools strengthens the translation of cognitive beliefs into behavioral intention. Qualitative findings complemented these quantitative patterns by revealing that readiness is conditional, ethically mediated, and situated within institutional constraints. Pre-service teachers framed AI as a tool that supports (rather than replaces) teacher expertise, and their intended use was contingent upon pedagogical clarity, ethical guidance, and formal training. The study contributes theoretically by specifying how professional knowledge translates into intention via acceptance beliefs, addressing a gap in prior research that examined TPACK and TAM separately. Practically, it advocates for pedagogy-centered AI preparation in teacher education, emphasizing instructional reasoning, ethical literacy, and experiential learning. Limitations include the single-institution sample and cross-sectional design, underscoring the need for longitudinal and comparative research. Ultimately, readiness for AI in ELT is not merely a matter of technology acceptance but a professionally mediated process that requires teacher education to cultivate critical, pedagogically grounded, and context-sensitive AI integration practices.

7-1- Limitations

- The single-case design used in this study restricted the extent of generalizability as the study was conducted in a single institution; replication in diverse Omani institutions and across other MENA countries is required. The census sample (n = 78), while appropriate for PLS-SEM in exploratory models, limits statistical power for detecting small effects and may not represent the broader population of pre-service English teachers regionally.
- The use of self-reported measures can be biased even when using validated measures; future research should include performance-based data and data based on observation.
- The cross-sectional design limits causality, thereby emphasizing the necessity of longitudinal studies.
- The survey-based qualitative data were limited in terms of depth; interviews and classroom-based approaches would provide a deeper insight.

7-2- Recommendations for Future Research

- Longitudinal and comparative studies should be done in the future to understand how competence-informed acceptance evolves over situations and career levels.
- Pedagogy-based AI training, ethical literacy training, and AI use practicum should be evaluated in intervention research.
- Additional research is also needed to investigate ethical preparedness, AI anxiety, and teacher identity as the complementary aspects of AI preparedness.
- The instructional effects would be explained by mixed method designs that involve classroom observations, teaching artifacts, and learning outcomes.

8- Declarations

8-1- Data Availability Statement

The data presented in this study are available in the article

8-2- Funding

The author received no financial support for the research, authorship, and/or publication of this article.

8-3- Institutional Review Board Statement

The study was approved by the Institutional Review Board (or Ethics Committee) of A’Sharqiyah University (ASU/UREBC/26/24).

8-4- Informed Consent Statement

Informed consent was obtained from all subjects involved in the study.

8-5- Conflicts of Interest

The author declares that there is no conflict of interest regarding the publication of this manuscript. In addition, the ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, and redundancies have been completely observed by the author.

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Appendix I

Table A1. Questionnaire on Pre-Service English Language Teachers' Readiness for AI Integration

Section	Construct / Dimension	Item Code	Item Statement	Response Scale
A	Demographic and Background Information	A1	Gender	Nominal
		A2	Age (years)	Open-ended
		A3	University name	Open-ended
		A4	Current year in programme	Categorical
B	Prior Experience with AI Tools (Moderator)	AIEX1	I have experience using AI tools for personal English language learning.	1 = No Experience to 5 = Extensive Experience
		AIEX2	I have used AI tools for lesson planning or material development.	1–5
		AIEX3	I have experience using AI tools to provide feedback on student writing or speaking.	1–5
		AIEX4	I have used AI tools for language analysis, discussion, or practice activities.	1–5
		AIEX5	Overall, I am familiar with AI tools used in English language teaching.	1–5
C	Content Knowledge (CK) – TPACK	CK1	I have a strong understanding of English grammar and syntax for teaching.	1 = Strongly Disagree to 5 = Strongly Agree
		CK2	I possess sufficient vocabulary knowledge for English language instruction.	1–5
		CK3	I understand discourse features of spoken and written English.	1–5
		CK4	I am knowledgeable about English phonology and pronunciation.	1–5
		CK5	I am confident in my overall English language content knowledge.	1–5
D	Pedagogical Knowledge (PK) – TPACK	PK1	I understand how learners acquire a second or foreign language.	1–5
		PK2	I can apply a variety of instructional strategies in English teaching.	1–5
		PK3	I know how to assess learners' English language skills effectively.	1–5
		PK4	I can adapt instruction to address learners' individual differences.	1–5
		PK5	I can manage an English language classroom effectively.	1–5
E	Technological Knowledge (TK) – TPACK	TK1	I can learn to use new AI tools easily.	1–5
		TK2	I am comfortable solving basic technical problems related to AI tools.	1–5
		TK3	I keep myself informed about new AI-based educational technologies.	1–5
		TK4	I have sufficient technical skills to use AI tools for teaching.	1–5
		TK5	I am familiar with a range of AI tools relevant to English teaching.	1–5
F	Perceived Usefulness (PU) – Mediator	PU1	Using AI tools would enhance my effectiveness as an English teacher.	1–5
		PU2	AI tools would improve the quality of my English teaching.	1–5
		PU3	AI tools would help me accomplish teaching tasks more efficiently.	1–5
		PU4	AI tools would support students' English language learning outcomes.	1–5
		PU5	Overall, AI tools would be useful in English language teaching.	1–5
G	Perceived Ease of Use (PEOU) – Mediator	PEOU1	Learning to use AI tools would be easy for me.	1–5
		PEOU2	I would find AI tools clear and understandable to use.	1–5
		PEOU3	Interacting with AI tools would not require much mental effort.	1–5
		PEOU4	I would find AI tools flexible and easy to operate.	1–5
		PEOU5	Overall, I believe AI tools would be easy to use in teaching.	1–5
H	Intended Future Use (IFU) – Outcome	IFU1	I intend to use AI tools to provide automated feedback on students' work.	1 = Extremely Unlikely to 5 = Extremely Likely
		IFU2	I intend to use AI tools to generate or adapt teaching materials.	1–5
		IFU3	I intend to use AI tools to support speaking and pronunciation practice.	1–5
		IFU4	I intend to use AI tools to teach vocabulary and grammar.	1–5
		IFU5	I intend to use AI tools to personalise students' English learning.	1–5
I	Open-Ended Questions (Qualitative)	OE1	Describe any experiences you have had using AI tools for learning or teaching English and how they influenced your views.	Open-ended
		OE2	In what ways could AI tools be useful for ELT? Provide examples.	Open-ended
		OE3	What aspects of AI tools would be easy or difficult for you to use as a future teacher? Why?	Open-ended
		OE4	How would you integrate AI tools into English lessons to support objectives or assessment?	Open-ended
		OE5	What challenges or concerns do you have about using AI in ELT?	Open-ended
		OE6	How well has your teacher-education programme prepared you to use AI tools, and what support is needed?	Open-ended
		OE7	How do you see your future role as an English teacher changing with AI use?	Open-ended
		OE8 (Optional)	What ethical or professional responsibilities should teachers consider when using AI?	Open-ended