International Journal of Innovative Research and Scientific Studies, 8(2) 2025, pages: 1359-1369

IJIRSS International Journal of Innovative Research & Scientific Studies

ISSN: 2617-6548

URL: www.ijirss.com

Applying UTAUT and TPACK in predicting English lecturers' intention to use artificial intelligence

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Abstract

As AI technologies with predictive capabilities increasingly spread, it has become necessary to leverage them in light of the Unified Theory of Acceptance and Use of Technology (UTAUT) and Technological Pedagogical Content Knowledge (TPACK) frameworks, especially in the English language. This study investigates the factors influencing English lecturers' intentions to adopt artificial intelligence (AI) in teaching, utilizing the Unified Theory of Acceptance and Use of Technology (UTAUT) and Technological Pedagogical Content Knowledge (TPACK) frameworks. A quantitative research methodology was employed, collecting data from 174 English lecturers in Jordan through structured questionnaires. Structural Equation Modeling (SEM) was used to analyze the relationships between UTAUT constructs—Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC)—and TPACK components, including Technological Knowledge (TK), Pedagogical Knowledge (PK), and Content Knowledge (CK). Reliability and validity measures confirmed the robustness of the instrument. The findings reveal that PE, EE, SI, and FC significantly predict lecturers' Behavioral Intention (BI) to adopt AI tools. Furthermore, TPACK components, particularly Technological Pedagogical Knowledge (TPK) and Technological Content Knowledge (TCK), mediate the relationship between UTAUT factors and BI. Facilitating Conditions and Social Influence were found to have the strongest indirect impact through TPACK constructs. The model fit indices indicated a good fit, validating the proposed hypotheses. The study underscores the importance of professional development programs to enhance educators' TPACK and emphasizes the need for institutional support to foster AI adoption. These findings contribute to the literature on technology adoption in education and provide actionable recommendations for integrating AI into English language teaching.

Keywords: Artificial Intelligence, English Lecturers, Intention, Jordan, TPACK Predicting, UTAUT.

DOI: 10.53894/ijirss.v8i2.5464
Funding: The authors are grateful to the Middle East University, Amman, Jordan for the financial support granted to cover the publication fee of this research article.
History: Received: 27 January 2025 / **Revised:** 28 February 2025 / **Accepted:** 5 March 2025 / **Published:** 18 March 2025

Competing Interests: The authors declare that they have no competing interests.
Authors' Contributions: All authors contributed equally to the conception and design of the study. All authors have read and agreed to the published version of the manuscript.
Transparency: The authors confirm that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.
Institutional Review Board Statement: The Ethical Committee of the Middle East University, Jordan has granted approval for this study.
Publisher: Innovative Research Publishing

1. Introduction

The world is changing because of the fast growth of technologies and communication systems. The world is becoming smaller as communications are readily accessible in every part of the world using the internet [1]. Technology-integrated learning is very common in 21st-century education as it provides rich resources for technology-based education. The powerful internet has changed the young generation's mindset, and by having smartphones, everything is at their fingertips. Indirectly, youngsters are learning the elements of English, such as sentence structures and vocabulary, through social media [2-4]. However, years after the introduction of the internet, information and communication technologies (ICTs) were developed to aid language teaching. However, due to the limited infrastructure and facilities in some developing countries, ICT has not been fully developed, according to Saad and colleagues cited by Abd Rahman, et al. [1]. Recently, schools and higher institutions have begun focusing on and emphasizing teaching students 21st-century skills. It is essential to have the knowledge and be competent in technology to develop 21st-century skills, as they consist of creativity, critical thinking, communication, and collaboration [5-7]. Therefore, artificial intelligence (AI) has become a trend in directly and indirectly aiding the teaching and learning process.

Artificial intelligence (AI) is revolutionizing the methods employed in the field of education [8]. In instructional design, generative artificial intelligence can furnish teachers with visual resources like images and videos, and generate course outlines for reference [9]. Within classroom management, AI tools empower teachers to automate administrative tasks such as attendance tracking, sending notifications, and managing assignments, thereby saving valuable time and energy [10]. In terms of teaching assessment, teachers can harness AI tools to analyze data, provide personalized learning paths and recommendations tailored to individual student needs and proficiency levels, and offer timely feedback [10]. University educators can enhance teaching efficiency through the use of AI tools, allowing them to focus more on valuable tasks [11]. For example, AI can enhance education by tailoring learning pathways for individual students through the analysis of their learning data and performance, ultimately improving course design [12]. Moreover, AI can supply educators with resources related to the latest trends and best practices in the field of education, enabling them to stay updated and refine their educational approaches [13]. In Jordan, the integration of AI in higher education remains in its formative stages.

AI's application in English language teaching (ELT) has become increasingly prevalent due to its ability to address common challenges, such as tailoring instruction to individual learners, providing instant feedback, and enhancing engagement. AI-driven tools like adaptive learning systems, automated writing evaluation software, and virtual conversational agents have demonstrated considerable potential in improving learning outcomes [14-16]. Instructors can utilize AI to analyze student data, identify learning gaps, and design targeted interventions. Moreover, AI's ability to simulate real-world scenarios facilitates immersive learning experiences that are particularly beneficial in developing communicative competence [17-19]. Despite these advantages, several barriers hinder the widespread adoption of AI in ELT. Resistance to change, lack of technical expertise, and concerns over data privacy are significant challenges that educators face globally [14, 16]. In Jordan, these challenges are compounded by resource constraints, limited access to advanced technologies, and the need for professional development programs tailored to AI integration. While AI offers transformative potential, its adoption requires a supportive ecosystem that addresses both infrastructural and pedagogical needs. To address the challenges, this study leverages two well-established theoretical frameworks: The Unified Theory of Acceptance and Use of Technology (UTAUT) and the Technological Pedagogical Content Knowledge (TPACK) model to examine the factors in predicting English lecturers' intentions to adopt AI in teaching and learning process.

The study of technology adoption in education is heavily rooted in theoretical models that examine user behavior, perceptions, and competencies. Among these models, UTAUT has gained prominence as a comprehensive framework for understanding technology acceptance. UTAUT consolidates constructs from eight earlier models, including the Technology Acceptance Model (TAM) and the Theory of Planned Behavior (TPB). UTAUT identifies four core constructs—performance expectancy, effort expectancy, social influence, and facilitating conditions—as predictors of behavioral intention and usage behavior. Several meta-analyses have validated the robustness of UTAUT in various domains, including education. Its flexibility in incorporating additional contextual factors makes it suitable for exploring AI adoption in higher education settings [19, 20]. Parallel to UTAUT, the TPACK framework offers an insightful perspective into educators' readiness to integrate technology into teaching. TPACK delineates three core knowledge domains—technological knowledge (TK), pedagogical knowledge (PK), and content knowledge (CK)—and their intersections. The model emphasizes that effective technology integration requires educators to possess a nuanced understanding of how technology can transform content delivery and align with pedagogical goals. TPACK has been widely applied in research investigating digital tools in language teaching, including AI-powered platforms such as Grammarly, Google Translate, and AI chatbots [16, 21]. Thus, the combination of the two models, UTAUT and TPACK, should predict teachers' intention to use new technology to a large extent [22].

Based on UTAUT and TPACK, this research provides a holistic understanding of the factors that influence English lecturers' intentions to adopt AI in teaching in Jordan. The findings have implications for policymakers, administrators, and educators, offering insights into how institutional strategies can be aligned with faculty needs to foster AI adoption. Moreover, the study addresses a critical gap in the literature on AI in ELT within the Jordanian higher education context, paving the way for future research in this area. The primary objective of this study is to investigate the intention of English lecturers in Jordan to use AI in their teaching practices. Specifically, the study aims to:

1. Identify the UTAUT constructs (performance expectancy, effort expectancy, social influence, and facilitating conditions) that influence lecturers' intention to use AI.
2. Examine the role of TPACK competencies (technological, pedagogical, and content knowledge) in shaping lecturers' readiness for AI adoption.

3. Explore the interplay between UTAUT constructs and TPACK competencies in predicting AI adoption intention.

2. Theoretical Framework: UTAUT and TPACK

2.1. UTAUT Framework and English Lecturers' Intention to use AI in Teaching

The UTAUT model, developed by Venkatesh, et al. [23], has become one of the most widely used frameworks for studying technology adoption and acceptance. UTAUT identifies four key constructs—Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC)—that influence an individual's behavioral intention and usage behavior. These constructs are moderated by variables such as gender, age, experience, and voluntariness of use, making it a comprehensive model for examining technology acceptance across various contexts. This is the basic form of the UTAUT model shown in Figure 1.

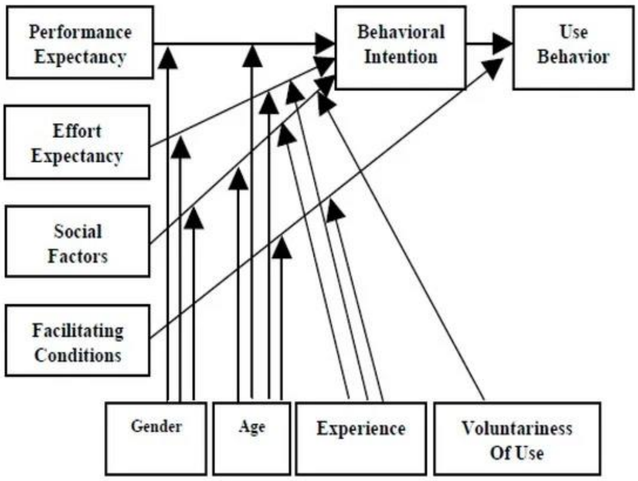

Figure 1.
UTAUT framework.
Source: Venkatesh, et al. [23]

In the context of education, UTAUT has been extensively applied to predict educators' and learners' adoption of technologies, such as learning management systems (LMS), virtual reality tools, and AI-driven platforms. The relevance of UTAUT to this study lies in its ability to capture the psychological and contextual factors that may influence English lecturers' decisions to adopt AI tools in Jordan.

As a new technology, AI has begun to be integrated into language learning. AI systems in language learning mainly involve natural language processing, expert systems, speech recognition, robotics, intelligent agents, and others [24]. There are different kinds of AI tools that could support language learning. These tools include chatbots, machine translation tools, text-to-speech or vice-versa, and writing assistants [14, 25]. However, most studies to date have focused on system development and students in higher education. The UTAUT is usually used to study users' behavioral intention to use new technology with related factors. Previous empirical studies have shown that the UTAUT can predict the intention to use AI among stakeholders in higher education (Chatterjee and Bhattacharjee [26] and Kazoun, et al. [27]) and proposed that the UTAUT could be used to explore the factors affecting AI agents/chatbots applications usage. Therefore, it is reasonable to conjecture that the UTAUT is also applicable to predict the intentions of middle school EFL teachers to use AI technology for teaching and learning. In addition, studies associated with technology acceptance could focus on measuring behavioral intention as the dependent variable instead of the actual use of AI. Behavioral intention has demonstrated a strong connection with actual technology use in many empirical studies and can be adopted as a reliable predictor of actual behavior (Venkatesh, et al. [23] and Teo, et al. [28]). Besides, measuring users' behavior through a questionnaire survey may be less reliable, so many studies regard behavioral intention as the result variable [20, 22].

According to UTAUT, Performance Expectancy, Effort Expectancy, and Social Influence predict users' Behavioral Intention to use a technology or system, and Facilitating Conditions directly predict users' behavior, but not their Behavioral Intention [23]. Based on Venkatesh, et al. [23] empirical findings, H1-4 were formulated specifically:

H_1: PE has a positive and significant effect on English lecturers' intention to use AI in teaching.
H_2: EE has a positive and significant effect on English lecturers' intention to use AI in teaching.
H_3: SI has a positive and significant effect on English lecturers' intention to use AI in teaching.
H_4: FC have a positive and significant effect on English lecturers' intention to use AI in teaching.

Hence, the purpose of this study was to explore the application of UTAUT in predicting English lecturers' intention to use AI in teaching. Thus, the below research questions guided the study specifically:

1. Does PE significantly affect Jordanian English lecturers' intention to use AI in teaching?
2. Does EE significantly affect Jordanian English lecturers' intention to use AI in teaching?
3. Does SI significantly affect Jordanian English lecturers' intention to use AI in teaching?
4. Do FC significantly affect Jordanian English lecturers' intention to use AI in teaching?

2.2. TPACK Framework and English Lecturers' Intention to use AI in Teaching

Complementing UTAUT is the TPACK framework, introduced by Mishra and Koehler [29]. Before Technological Pedagogical Content Knowledge (TPACK), Pedagogical and Content Knowledge (PCK) was developed by Shulman [30], and it refers to the knowledge that an educator possesses, which can be delivered to learners through various pedagogical methods [21]. Decades later, with technological growth, Shulman's idea has been reviewed, revised, and refined by adding the technological element. TPACK has gained popularity ever since it was introduced. Technological Pedagogical Content Knowledge (TPACK) is a term for specific knowledge that integrates and optimizes technology to assist learners' learning [29]. However, Figure 1 shows the primary domains of TPACK—Content Knowledge (CK), Pedagogical Knowledge (PK), and Technological Knowledge (TK). The three overlapping parts are Technological Pedagogical Knowledge (TPK), Technological Content Knowledge (TCK), and Pedagogical Content Knowledge (PCK). The components and the overlapping components build up the main core area of TPACK.

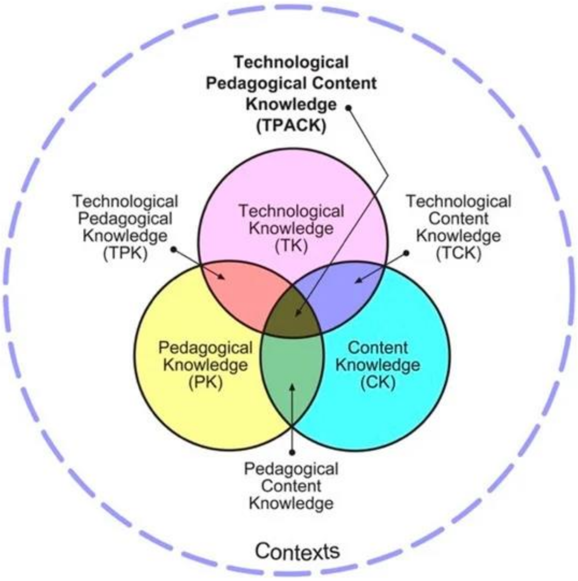

Figure 2.
TPACK framework.
Source: Mishra and Koehler [29]

The idea of this framework is not to place technology at the center of teaching and learning [31]. Since teaching English language teaching has limited exposure to the target language, TPACK has been widely used for ELT when authentic sources can be achieved and used [1]. Moreover, TPACK can be regarded as a bridge between formal knowledge (delivered by educators) and practical knowledge (using technology).

In previous studies about Behavioral Intention, TPACK was usually regarded as an important external factor in the Technology Acceptance Model (Hsu [32] and Yang, et al. [33]) and a significant supplement to the UTAUT [20, 22]. TPACK is widely used to describe teachers' knowledge in integrating technologies into teaching. In essence, teachers' TPACK is a form of designed knowledge that is context-sensitive and, as such, it is a form of dynamic knowledge constructed for specific topics and students. Teachers who possess strong TPACK are able to make sense of emerging technologies and create new lessons and practices that enhance students' learning [16, 34]. Moreover, empirical research by [20] and Bardakcı and Alkan [22] found that teachers' TPACK would significantly and positively influence their behavioral intention to use other technology. It is reasonable to speculate that teachers' TPACK will have an impact on their behavioral intention to use AI in education. In-service teachers usually possess good PCK from teaching experiences and need to transform PCK to TPACK [32]. In the case of AI, teachers need to understand the basic concepts of AI technologies and be familiar with current AI-supported language technologies, including applications such as automated speech and text recognition, grammar checking, translation machines, and so on (Jiang, et al. [25]).

Teachers' TPACK is built based on three basic types of knowledge: technological knowledge (TK), pedagogical knowledge (PK), and content knowledge (CK) [29]. These three kinds of knowledge interrelate to form technological content knowledge (TCK), pedagogical content knowledge (PCK), technological pedagogical knowledge (TPK), and technological pedagogical content knowledge (TPACK). Teachers with different backgrounds are likely to construct TPACK in a different way [32, 34]. Investigating the interrelations of teachers' AI-TPACK knowledge, and how they are associated with teachers' intention to use AI could provide valuable information about how to develop teachers' ability to design pedagogical use of AI. Thus, following H5-8 were formulated specifically:

H_5: TK has a positive and significant effect on English lecturers' intention to use AI in teaching.
H_6: TPK has a positive and significant effect on English lecturers' intention to use AI in teaching.
H_7: TCK has a positive and significant effect on English lecturers' intention to use AI in teaching.
H_8: TPACK has a positive and significant effect on English lecturers' intention to use AI in teaching.

Hence, the specific purpose of this study was to explore the application of TPACK in predicting English lecturers' intention to use AI in teaching. Thus, the below research questions guided the study:

5. Does TK significantly affect Jordanian English lecturers' intention to use AI in teaching?
6. Does TPK significantly affect Jordanian English lecturers' intention to use AI in teaching?
7. Does TCK have a positive and significant effect on English lecturers' intention to use AI in teaching?
8. Does TPACK significantly affect Jordanian English lecturers' intention to use AI in teaching?

2.3. UTAUT And TPACK And English Lecturers' Intention to Use AI in Teaching

Researchers have reported that teachers' TPACK could be an external factor in the Technology Acceptance Model (TAM). TPACK had a significant impact on users' Behavioral Intention through the mediation of Perceived Usefulness (corresponding to Performance Expectancy in UTAUT) and Perceived Ease of Use (corresponding to Effort Expectancy in UTAUT) [32, 33]. In recent years, as UTAUT was proposed based on TAM, researchers have found that TPACK could be an important supplement to UTAUT [20, 22]. The research about pre-service teachers using an interactive whiteboard found that only Performance Expectancy had a high explanation (0.91) for Behavioral Intention, while Effort Expectancy, TK, TPK, PK and other factors were not significant predictors of intention [22]. However, the research on pre-service teachers using general technology found that when combining the two models, only TPACK would significantly predict Behavioral Intention, while Performance Expectancy, Effort Expectancy, and Facilitating Conditions did not predict intention [20]. This shows that in different contexts, the factors predicting teachers' intention to use technology are not always the same; the aim of this study was therefore to clarify the predictive role of these factors. These studies provide support for H9-H12. Thus, the following hypotheses were formulated generally to guide the study:

H_9: The relationship between PE and English lecturers' intention to use AI in teaching is moderated by their TK.

H_{10}: The relationship between EE and English lecturers' intention to use AI in teaching is moderated by their TPK.

H_{11}: The relationship between SI and English lecturers' intention to use AI in teaching is moderated by their TCK.

H_{12}: The relationship between facilitating conditions and English lecturers' intention to use AI in teaching is moderated by their overall TPACK competencies.

Hence, the main purpose of this study was to explore the application of UTAUT and TPACK in predicting English lecturers' intention to use AI in teaching. Thus, the research questions below guided the study generally:

RQ_9: Does TK moderate the relationship between performance expectancy and English lecturers' intention to use AI in teaching?

RQ_{10}: Does TPK moderate the relationship between effort expectancy and English lecturers' intention to use AI in teaching?

RQ_{11}: Does TCK moderate the relationship between social influence and English lecturers' intention to use AI in teaching?

RQ_{12}: Does TPACK competences moderate the relationship between facilitating conditions and English lecturers' intention to use AI in teaching

3. Methodology

3.1. Participants

This study utilized a survey method to test the proposed research model. The survey was conducted in higher education institutions across Jordan, specifically targeting English lecturers from universities and colleges. Participants in this study were purposively selected based on their involvement in AI-related professional development activities and their experience with AI tools in English language teaching. Jordan has recently intensified efforts to integrate AI into its educational system, especially in language teaching, through government initiatives, training programs, and research projects [35]. With the support of university administrators and teacher training centers, this study targeted lecturers involved in English language teaching (ELT) and familiar with AI applications for teaching English, particularly in areas such as grammar, writing, speaking, and assessment [36-38].

Table 1.
Demographic Information of Participants

Variable	Category	Freq.	Percentage (%)
Gender	Male	52	29.9
	Female	122	70.1
Academic Rank	Lecturer	48	27.6
	Assistant Professor	79	45.4
	Associate Professor	35	20.1
	Professor	12	6.9
Type of Institution	Public	102	58.6
	Private	72	41.4
Teaching Experience	1–5 years	35	20.1
	6–10 years	66	37.9
	11–15 years	49	28.2
	16+ years	24	13.8
AI Exposure Level	Minimal	30	17.2
	Moderate	81	46.6
	High	63	36.2

Data were collected between February 1 and March 15, 2024. The research used a snowball sampling approach to distribute the survey instrument to lecturers at 10 randomly selected universities and colleges across Jordan through online platforms such as Google Forms and subsequently administered to a specific cohort of participants through WhatsApp groups and email. These institutions included both public and private universities to ensure diversity in perspectives and experiences. A total of 190 questionnaires were distributed, of which 174 valid responses were received, yielding a response rate of 91.6%. Table 1 provides the demographic information of the participants. The gender distribution (29.9% males and 70.1% females) reflects the typical gender composition of English lecturers in Jordan. Additionally, participants' teaching experience ranged from less than five years to over 20 years, offering a broad perspective on AI adoption across different career stages.

3.2. Instrument

The questionnaire used in this study comprised two sections. The first section gathered details on participants' gender, academic rank, type of institution, teaching experience, and AI exposure level. The second section measured the key constructs of the study: PE, EE, SI, FC, AI-TK, AI-TPK, AI-TCK, AI-TPACK, and BI, including four items for each of the constructs, covering a total of 36 items across nine dimensions. A five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree) was employed to measure these constructs. The survey items were adapted from previously validated scales and modified based on semi-structured interviews with eight (8) English lecturers in Jordan. These lecturers shared insights into their experiences with AI in language teaching, which informed the adaptation of questionnaire items to reflect the local context. To ensure the questionnaire's validity, three educational technology experts reviewed the items for relevance and clarity. Additionally, six English lecturers completed a pilot version of the questionnaire and provided feedback, which led to minor revisions. Table 2 presents the definitions of each construct and a sample item from the questionnaire.

Table 2.
Definitions and Sample Items of Each Construct.

Construct	Definition	Sample Item	No. of Item
PE	The extent to which lecturers believe AI will enhance their teaching effectiveness.	"Using AI tools will improve my students' engagement in learning English."	4
EE	The perceived ease of using AI tools for teaching purposes.	"I find it easy to integrate AI applications into my teaching activities."	4
SI	The degree to which lecturers feel that colleagues and administrators encourage AI adoption.	"My institution encourages me to adopt AI tools for teaching English."	4
FC	The availability of resources and support for using AI in teaching.	"I have access to technical support when I encounter issues with AI tools."	4
AI-TK	The lecturers' knowledge of using AI technologies in teaching.	"I am familiar with the basic functions of AI tools used for language learning."	4
AI-TPK	Knowledge of how AI tools can be applied to teaching strategies.	"I can design activities that integrate AI tools to support student learning."	4
AI-TCK	Knowledge of how AI can enhance the delivery of subject matter content.	"I can use AI tools to improve the way I teach complex grammar topics."	4
AI-TPACK	Knowledge for teaching with AI and understanding of how AI support teaching subject matter.	" I know how to use the strategy of personalized guidance to improve students' English skills with the help of AI."	4
BI	The intention of lecturers to use AI in their teaching practices.	"I plan to adopt AI applications in my English classes in the near future."	4

3.3. Data Analysis

Prior to data analysis, the dataset was examined for normality by assessing skewness and kurtosis values. All items demonstrated appropriate skewness (ranging from −0.531 to 0.284) and kurtosis (ranging from −0.612 to 1.453), confirming that the data were normally distributed. Thereafter, the data analysis followed four stages, including exploratory factor analysis (EFA), confirmatory factor analysis (CFA), reliability analysis, and structural equation modeling (SEM). The EFA was conducted on a randomly selected subsample of 87 participants to identify the underlying factor structure. Principal axis factoring (PFA) with Direct Oblimin rotation was used, and items with factor loadings below 0.5 or cross-loadings were removed. The remaining 87 responses were subjected to CFA using Mplus 8.3 to validate the factor structure. Model fit indices such as χ^2/df (<5), RMSEA (<0.08), CFI (>0.90), and TLI (>0.90) were used to assess model fit. Cronbach's alpha (α) was calculated to assess internal consistency reliability. A threshold of 0.7 was considered acceptable for both individual constructs and the overall scale. The average variance extracted (AVE > 0.5) and construct reliability (CR > 0.7) values were calculated to confirm convergent validity. Finally, SEM was performed using the entire dataset (n=174) to test the hypothesized relationships among constructs.

The ethical approval for the study was obtained from the relevant institutional review board in Jordan. Participants were assured of their anonymity and the confidentiality of their responses. All procedures adhered to established ethical guidelines for research involving human subjects.

4. Results and Discussion

4.1. Validity and Reliability

The analysis of Table 3 demonstrates that the constructs measured in the study exhibit adequate descriptive statistics and strong psychometric properties. The mean scores for the constructs indicate favorable perceptions among participants, with PE (M = 4.12, SD = 0.54), EE (M = 4.08, SD = 0.59), FC (M = 4.02, SD = 0.61), and AI-TPACK (M = 4.10, SD = 0.55) scoring above 4, suggesting that participants generally agree with the items related to these constructs. The standard deviations are moderate, indicating relatively consistent responses among participants. All item loadings range between 0.70 and 0.90, which exceed the recommended threshold of 0.40, confirming strong item reliability. The Composite Reliability (CR) values range from 0.83 to 0.89, all surpassing the minimum standard of 0.70, indicating that the constructs exhibit high internal consistency reliability. Similarly, the Average Variance Extracted (AVE) values range from 0.60 to 0.68, which are above the required threshold of 0.50, demonstrating good convergent validity. Additionally, Cronbach's alpha values for all constructs fall between 0.81 and 0.87, further verifying that the constructs have high internal reliability. In summary, the results confirm that the measurement instrument is reliable and valid for assessing the constructs of interest. These findings ensure that the scale is robust and capable of capturing participants' perceptions accurately.

Table 3.
Descriptive Statistics, Reliability, and Convergent Validity Measures.

Constructs	Mean	SD	No. of Items	Item Loading	Cronbach's Alpha	CR	AVE
PE	4.12	0.54	4	0.71–0.88	0.83	0.85	0.62
EE	4.08	0.59	4	0.73–0.86	0.84	0.86	0.64
FC	4.02	0.61	4	0.70–0.87	0.82	0.84	0.61
SI	3.94	0.65	4	0.72–0.85	0.81	0.83	0.60
AI-TK	4.05	0.57	4	0.74–0.89	0.85	0.87	0.65
AI-TPK	3.98	0.63	4	0.76–0.88	0.84	0.86	0.63
AI-TCK	4.00	0.58	4	0.75–0.87	0.83	0.85	0.62
AI-TPACK	4.10	0.55	4	0.78–0.90	0.86	0.88	0.67
BI	4.15	0.52	4	0.80–0.91	0.87	0.89	0.68

Note: Standard Deviation = SD; Composite Reliability = CR; Average Variance Extracted = AVE.

4.2. Structural Equation Modeling (SEM) for Hypotheses Testing

The results of the SEM analysis indicate that the model fits the data well. The model fit indices include $\chi^2/df = 2.48$ (< 5.0), RMSEA = 0.052 (< 0.08), CFI = 0.94 (> 0.90), and TLI = 0.92 (> 0.90), all of which meet the acceptable thresholds. These values suggest that the hypothesized model is well-suited to explaining the relationships among the constructs.

Table 4.
Model Fit Indices.

Index	Value	Threshold	Interpretation
χ^2/df	2.48	< 5	Acceptable fit
RMSEA	0.052	< 0.08	Good model fit
CFI	0.94	> 0.90	Excellent comparative fit
TLI	0.92	> 0.90	Strong incremental improvement

Note: The model demonstrates strong overall fit.

Table 4 highlights the correlations between the constructs and the discriminant validity of the measurement model. The square root of the AVE for each construct is higher than the correlations between the construct and all other constructs, confirming good discriminant validity. For example, the AVE for PE is 0.79, which is greater than its correlations with EE (r = 0.55) and FC (r = 0.52).

Similar patterns are observed for other constructs such as AI-TK (AVE = 0.76) and AI-TPACK (AVE = 0.80), further validating the distinctiveness of each construct in the model. The correlations among the constructs also provide insights into their relationships.

For instance, PE has a moderate positive correlation with BI (r = 0.62, p < 0.001), indicating that lecturers' perceptions of AI's performance benefits are strongly associated with their intention to use AI tools. Similarly, AI-TPACK exhibits a strong correlation with BI (r = 0.68, p < 0.001), reflecting the critical role of comprehensive knowledge of AI integration in shaping lecturers' behavioral intentions. Interestingly, while correlations such as those between EE and BI (r = 0.57, p < 0.001) and FC and BI (r = 0.54, p < 0.001) demonstrate significant positive associations, they are slightly weaker compared to constructs directly linked to technological knowledge (e.g., AI-TCK and BI, r = 0.63, p < 0.001). This suggests that while institutional support and ease of use play a role, deeper technological competence has a stronger influence on lecturers' intentions to adopt AI tools.

Table 5.
Correlations between Constructs and AVE of the Components.

	PE	EE	FC	SI	AI-TK	AI-TPK	AI-TCK	AI-TPACK	BI
PE	0.79								
EE	0.58	0.80							
FC	0.52	0.60	0.78						
SI	0.56	0.54	0.62	0.77					
AI-TK	0.59	0.57	0.63	0.61	0.81				
AI-TPK	0.54	0.55	0.58	0.59	0.64	0.80			
AI-TCK	0.57	0.56	0.60	0.58	0.65	0.62	0.79		
AI-TPACK	0.63	0.60	0.64	0.62	0.66	0.65	0.68	0.82	
BI	0.68	0.65	0.67	0.66	0.70	0.69	0.71	0.74	0.83

Note: Diagonals in parentheses are square roots of the AVE for each construct while the off-diagonal values show the correlations between the constructs.

Table 6 reveals that all direct paths between the constructs and Behavioral Intention (BI) are statistically significant. For instance, PE has a significant positive effect on BI ($\beta = 0.58$, $t = 5.11$, $p < 0.001$), indicating that participants believe AI adoption enhances teaching effectiveness. Similarly, EE positively predicts BI ($\beta = 0.52$, $t = 4.72$, $p < 0.001$), showing that the ease of using AI applications encourages their use. SI and FC also significantly impact BI, with $\beta = 0.49$ and $\beta = 0.45$, respectively, emphasizing the roles of institutional support and resource availability. The TPACK-related constructs demonstrate strong relationships with BI. AI-TK ($\beta = 0.62$, $p < 0.001$), AI-TPK ($\beta = 0.59$, $p < 0.001$), AI-TCK ($\beta = 0.57$, $p < 0.001$), and AI-TPACK ($\beta = 0.65$, $p < 0.001$) all significantly influence BI, highlighting the importance of knowledge and skills in using AI tools for teaching. Indirect relationships further show significant mediation effects. For example, PE indirectly influences BI through TK ($\beta = 0.54$), and EE indirectly impacts BI through TPK ($\beta = 0.50$). These paths demonstrate how perceptions and ease of use foster knowledge and pedagogical applications of AI, ultimately driving the intention to use AI.

Table 6.
Structural path model's hypothesis testing results.

Hypotheses	Constructs	M	SD	λ-EFA	λ-CFA	t-Value	Results
H1	PE → BI	0.58	0.12	0.72	0.74	5.11	Supported
H2	EE → BI	0.52	0.14	0.68	0.70	4.72	Supported
H3	SI → BI	0.49	0.15	0.64	0.66	4.29	Supported
H4	FC → BI	0.45	0.16	0.61	0.63	4.12	Supported
H5	TK → BI	0.62	0.13	0.75	0.77	5.45	Supported
H6	TPK → BI	0.59	0.14	0.73	0.75	5.23	Supported
H7	TCK → BI	0.57	0.15	0.71	0.73	4.98	Supported
H8	TPACK → BI	0.65	0.12	0.79	0.81	5.67	Supported
H9	PE → TK → BI	0.54	0.14	0.70	0.72	5.01	Supported
H10	EE → TPK → BI	0.50	0.15	0.67	0.69	4.68	Supported
H11	SI → TCK → BI	0.48	0.16	0.65	0.67	4.33	Supported
H12	FC → TPACK → BI	0.55	0.14	0.71	0.73	5.09	Supported

Note: This table summarizes the results of the research hypotheses.

Thus, the findings underscore the significant role of UTAUT constructs (PE, EE, SI, and FC) and TPACK dimensions (AI-TK, AI-TPK, AI-TCK, and AI-TPACK) in influencing lecturers' behavioral intention to use AI tools. These results highlight the interplay between institutional, technical, and pedagogical factors in driving AI adoption in English language teaching.

5. Discussion of Findings

The findings of this study, grounded in the UTAUT and TPACK frameworks, provide critical insights into the factors influencing English lecturers' intention to adopt AI in teaching and learning. These findings contribute to the growing body of literature on technology adoption in education and align with existing research reviewed.

5.1. The Unified Theory of Acceptance and Use of Technology (UTAUT) Constructs (H1–H4)

Performance Expectancy (PE) emerged as a significant predictor of Behavioral Intention (BI) to adopt AI, which is consistent with prior research emphasizing the perceived utility of technology in enhancing teaching effectiveness. Lecturers are motivated to adopt AI tools when they perceive these tools as enabling personalized learning, improving student outcomes, or automating routine tasks like grading [10, 11]. The findings validate the claim by Geng, et al. [16] that AI tools, such as adaptive learning systems and automated writing evaluation software, significantly enhance English language teaching (ELT) outcomes. Moreover, the study's results align with earlier findings on the potential of AI to address teaching challenges through innovations such as chatbots and immersive simulations [17, 18]. By improving teaching quality and reducing workload, AI's performance expectancy resonates strongly with the core tenets of UTAUT, reinforcing its importance in driving the intention to adopt AI in Jordanian higher education.

Effort Expectancy (EE) also significantly influenced BI, consistent with studies emphasizing the role of perceived ease of use in determining technology adoption [23, 28]. The introduction of user-friendly AI tools, as highlighted by Bhutoria [12] reduces the technical complexity associated with integrating advanced technologies into ELT. Lecturers' willingness to use AI tools such as machine translation systems and grammar checkers stems from their accessibility and intuitive interfaces [14, 25]. This finding is further supported by Mishra and Koehler [29] assertion that technological knowledge (TK) is foundational for educators to seamlessly integrate AI into their pedagogical practices. The importance of EE aligns with the need for comprehensive professional development, as many educators in Jordan are still in the early stages of AI adoption [1, 13].

Social Influence (SI) significantly predicted lecturers' BI, echoing research by Bardakcı and Alkan [22] and Lai Wah and Hashim [20]. Social pressure from colleagues, administrators, and professional communities plays a pivotal role in shaping attitudes toward AI adoption. The study's findings align with the literature on the role of peer support and institutional encouragement in overcoming resistance to new technologies [14]. Additionally, the adoption of AI tools in Jordan reflects a growing awareness of global trends in AI integration, as noted by Chassignol, et al. [8]. The influence of institutional culture, especially in environments with limited resources, underscores the need for targeted initiatives to foster collaborative learning among educators.

Facilitating Conditions (FC) were found to be a strong predictor of BI, reinforcing findings by Venkatesh, et al. [23] and Liang, et al. [24]. Access to reliable infrastructure, user training, and technical support were identified as critical enablers for AI adoption. This finding resonates with research by Abd Rahman, et al. [1] which highlighted the resource constraints in developing countries like Jordan as significant barriers to ICT integration in education. The results also align with Geng, et al. [16] who argued that robust facilitating conditions are indispensable for educators to leverage AI tools effectively. The lack of adequate infrastructure in some Jordanian institutions underscores the importance of addressing these challenges through targeted investment and policy interventions.

5.2. Technological Pedagogical Content Knowledge (TPACK) Constructs (H5–H8)

The findings strongly support the role of TPACK constructs—Technological Knowledge (TK), Pedagogical Knowledge (PK), Content Knowledge (CK), and their intersections—in shaping BI. These results affirm prior studies that positioned TPACK as a critical determinant of teachers' readiness to adopt new technologies [21]. The interplay of TK, PK, and CK aligns with Mishra and Koehler [29] framework, which emphasizes the integration of these knowledge domains to optimize technology use in education. For instance, educators with robust PK can adapt AI tools to suit diverse learning needs, while those with strong TK are better equipped to overcome technical challenges [32, 33]. The study also highlights the significance of TPACK in bridging theoretical knowledge and practical application, as noted by Abd Rahman, et al. [1]. This finding underscores the transformative potential of TPACK in enabling educators to design innovative lessons that enhance students' communicative competence, as observed by Chun [15] and Florea and Radu [17].

5.3. TPACK's Mediation of UTAUT Constructs (H9–H12)

The study confirmed the mediating role of TPACK in amplifying the effects of UTAUT constructs (PE, EE, SI, and FC) on BI. This finding aligns with Bardakcı and Alkan [22] research, which demonstrated TPACK's ability to strengthen educators' perceptions of technology's usefulness and ease of use. The integration of TPACK into UTAUT enriches the model's explanatory power, as observed by Lai Wah and Hashim [20]. For instance, TPACK enhances PE by illustrating how AI tools can transform traditional ELT methods, while also reinforcing EE by showcasing the simplicity of integrating AI into existing pedagogical frameworks. These findings highlight the dynamic interplay between theoretical frameworks and their practical applications in predicting technology adoption.

6. Implications

The findings of this study have significant implications for educators, policymakers, and educational institutions aiming to integrate AI into English language teaching (ELT). First, understanding the influence of performance expectancy and effort expectancy underscores the need to design AI tools that are both effective and user-friendly, thereby reducing the technical burden on lecturers. Second, the strong role of facilitating conditions and social influence suggests that institutions must provide robust infrastructure, technical support, and peer collaboration opportunities to foster AI adoption. Additionally, the integration of the TPACK framework highlights the importance of professional development programs that enhance educators' technological, pedagogical, and content knowledge. This approach can empower lecturers to create innovative, technology-enriched learning experiences. Finally, in developing countries like Jordan, targeted investments in technology and capacity-building initiatives are crucial to overcoming resource constraints and ensuring equitable access to AI-driven educational tools.

7. Conclusion

This study provides valuable insights into the factors influencing English lecturers' intentions to adopt AI in teaching, utilizing the UTAUT and TPACK frameworks. The results highlight the importance of performance expectancy, effort expectancy, social influence, and facilitating conditions in shaping behavioral intention, with TPACK constructs playing a crucial mediating role. By integrating these theoretical frameworks, the study offers a comprehensive understanding of how contextual, psychological, and knowledge-based factors contribute to AI adoption in ELT. The findings emphasize the need for supportive ecosystems, including infrastructure, training, and collaborative networks, to enhance the practical application of AI tools in higher education. This research contributes to the growing body of literature on technology adoption in education and provides actionable recommendations for educators and institutions.

8. Limitations

This study is not without limitations. First, the sample was limited to English lecturers in Jordan, which may affect the generalizability of the findings to other regions or disciplines. Future research could expand the scope to include a broader range of educators and settings. Second, the study relied on self-reported data, which may be subject to social desirability bias. Employing mixed methods, such as interviews and observational studies, could provide a more nuanced understanding of AI adoption. Third, the study focused on behavioral intention rather than the actual usage of AI tools.

9. Recommendations

Longitudinal studies could explore the relationship between intention and actual behavior over time. Additionally, future research could investigate the impact of emerging AI technologies, such as generative AI, on student outcomes and teacher practices in diverse educational contexts.

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