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Adoption of Artificial Intelligence Tools for English Language Learning Among Saudi EFL University Students: The Moderating Role of Faculty

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Abstract

Purpose: This study explores the adoption of AI tools by Saudi EFL (English as a Foreign Language) learners using an extended Technology Acceptance Model (TAM). The research integrates additional factors such as perceived knowledge, engagement, and motivation to understand their influence on Saudi EFL university students' acceptance of AI tools. Research Method: Employing a cross-sectional survey design, data were gathered from 472 EFL students at King Saud University using a simple random sampling technique. The data were analyzed using Structural Equation Modeling (SEM) via AMOS (Version 29) in two stages: the measurement model and the structural model. Findings: The measurement model confirmed the reliability and validity of the study's constructs. The structural model tested the hypothesized relationships, revealing that perceived knowledge, engagement, and motivation significantly affect the perceived usefulness (PU) and perceived ease of use (PEoU) of AI tools among Saudi EFL learners. Both PU and PEoU were found to significantly influence students' behavioral intention to adopt AI tools for language learning. However, no moderating effect was found for faculty in the relationship between students' perception (PU and PeoU) and their intention to adopt IA tools. Collectively, these external variables explained 35% of the variance in PU, 43% in PEoU, 65% in the intention to adopt AI, and 36% in the actual adoption of AI tools. Significance: This research represents a pioneering effort within the Saudi educational context. By extending the TAM model to include perceived knowledge, engagement, and motivation, the study provides valuable insights into factors that influence the adoption of AI tools in English language learning. These findings can guide educators, universities, and language centers in developing strategies to enhance AI tool adoption, thereby making language learning more accessible and effective for students..

Keywords: *Artificial Intelligence Tools, EFL Students, Extended TAM, Structural Equation Modelling, Saudi Arabia.*

Introduction

Artificial intelligence (AI) is revolutionizing various sectors by enhancing automation with intelligent actions (Stahl et al., 2023). Artificial Intelligence (AI) holds significant promise in revolutionizing teaching and learning methodologies within the educational sphere. AI technologies like Chatbots and Artificial General Intelligence (AGI) can enhance pedagogy, enable personalized learning, improve assessment methodologies, and provide tailored learning experiences for students (Adiguzel et al., 2023; Geldbach, 2023). By leveraging AI in education, educators can benefit from reduced planning time, improved teaching outcomes, and increased student engagement, while students can enjoy personalized learning experiences and improved educational outcomes.

AI brings new possibilities to improve the effectiveness and caliber of instruction in English as a Foreign Language (EFL) classrooms (Chun, 2020). Learner satisfaction is increased by AI technologies like data mining, which allow for individualized learning experiences and instant feedback (Pokrivcakova, 2019). According to emerging research, artificial intelligence (AI) is either supplementing or replacing a few conventional EFL teaching duties, including as homework checking, test marking, learner analysis (Tlili et al., 2021), and writing and pronunciation correction (Florea & Radu, 2019).

However, the integration of AI in education also raises ethical concerns, such as the risk of cheating and the importance of responsible and equitable implementation to ensure quality education for all learners (Ayala-Pazmiño, 2023; Balta, 2023). Within the educational sphere, AI has the potential to fundamentally transform teaching and learning methodologies. However, existing research predominantly focuses on the technical development of AI systems (Divekar et al., 2021), with insufficient emphasis on the factors

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influencing AI adoption in language learning environments (Zawacki-Richter et al., 2019). Only recently has scholarly attention shifted towards understanding educators' perceptions of AI in educational contexts (Chiu & Chai, 2020).

The integration of AI tools in language learning has garnered significant interest, offering personalized and adaptive learning experiences (Zou et al., 2020). Nevertheless, the adoption of these tools among Saudi EFL learners remains underexplored, despite their potential to significantly enhance language proficiency (Viberg & Andersson, 2021). Identifying the variables that predict the acceptance and utilization of AI-powered language learning tools is crucial for developing effective strategies to promote their adoption and optimize their educational impact (Shadiev et al., 2022). A comprehensive understanding of these determinants can give constructive insights for educators, policymakers, and technology developers to tailor AI tools to the specific needs and preferences of Saudi EFL learners (Almushayt, 2022).

Although AI has a great deal of potential to help EFL students learn, incorporating new technologies into the classroom requires overcoming many obstacles (Tsai & Chai, 2012). Adapting to AI and using it to improve teaching and learning presents several issues for EFL teachers and students. The creation of creative lesson plans and the acceptance of AI-supported language learning by educators and students are prerequisites for its effective implementation (Song & Song, 2023; Geng et al., 2021). Foreign language instructors' express concerns about a range of external variables, including a lack of knowledge and skills, contradictory beliefs, and a fear of losing their pedagogical positions, even if they typically support the use of modern technology in the classroom (Alharbi, 2024; Pokrivcakova, 2019). Therefore, while incorporating AI into EFL classes, it is crucial to research students' acceptance of AI as well as the associated internal and external issues.

In the context of language learning in Saudi Arabia, the integration of technology, particularly in English language instruction, has received significant attention (Alahmadi & Alraddadi, 2020; Hashmi, 2016). Studies indicate that AI technologies like chatbots, computer-based feedback systems, and writing assistants positively impact the English language teaching and learning process (Alhalangy & AbdAlgane, 2023; Mohammed et al., 2023; Alnasser, 2022). Saudi EFL students and teachers perceive AI as beneficial for improving English language learning outcomes, particularly in traditional educational settings where students face challenges due to outdated teaching methods (Aljohani, 2021). However, the utilization of AI tools in English language instruction has encountered several challenges. Research has highlighted issues such as insufficient knowledge and training, along with negative attitudes towards technology use in classrooms (Alahmadi & Alraddadi, 2020; Hashmi, 2016; Alharbi, 2024).

The integration of Artificial Intelligence (AI) tools in educational settings, particularly for enhancing English as a Foreign Language (EFL) learning, has gained significant traction in recent years (Steffens et al., 2021). However, there remains a paucity of research investigating the factors influencing the adoption of these technologies among EFL learners in Saudi Arabia. While the Technology Acceptance Model (TAM) has been extensively utilized to explore technology adoption across various contexts, its specific application to AI tools in the Saudi EFL educational environment is underexplored (Alhalangy & AbdAlgane, 2023; Mohammed et al., 2023; Alnasser, 2022). Existing studies in Saudi Arabia largely provide descriptive insights into the use of AI tools in language learning, without delving deeply into the determinants that affect learners' acceptance and adoption of these technologies (Jamshed et al., 2024; Syed & Al-Rawi, 2023; Mousavi et al., 2023; Alotaibi, & Alshehri, 2023). Moreover, traditional TAM models often overlook critical variables such as perceived knowledge, engagement, and motivation, which could play pivotal roles in shaping learners' attitudes towards AI tools (Alharbi, 2024). These factors are particularly relevant in the Saudi context, where cultural and educational dynamics can significantly impact technology acceptance. By employing empirical study utilizing Structural Equation Modeling (SEM) for the hypothesized model analysis, this study seeks to:

1. Examine the influence of perceived knowledge, engagement, and motivation on the PU and PEoU of AI tools among Saudi EFL learners.

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2. Analyze how these perceptions subsequently affect their behavioral intention and actual adoption of AI tools in their language learning process.

The findings of this study are expected to fill the existing research gap by providing empirical evidence on the determinants of AI tool adoption in the Saudi EFL context. This research not only advances the theoretical framework of TAM but also offers practical implications for educators, policymakers, and institutions in Saudi Arabia. Understanding these factors can inform the development of more effective strategies to support EFL learners in embracing AI technologies, thereby enhancing their language learning experience and outcomes.

Conceptual Frameworks

Davis (1989) created TAM, which serves as the conceptual foundation for the study. It is well known for its comprehension of how users accept and use technology. According to TAM, PU and PEoU are important variables influencing users' tendency to embrace technology. While PU is a measure of users' conviction in the technology's capacity to enhance performance and facilitate goal achievement, PEOU gauges how users feel about the technology's simplicity and ease of use. Prior research (Vărzaru et al., 2021; Santoso, 2017) has shown that both PU and PEOU have a significant impact on consumers' opinions and intentions about the adoption of technology.

There are various reasons why TAM was chosen as the theoretical basis. First, TAM is a great option because of its simplicity and brevity (Drueke et al., 2021). Second, as demonstrated by Al-Emran et al. (2018), TAM has continuously demonstrated its usefulness in m-learning situations, demonstrating its effectiveness in gauging the take-up of online learning (Khanh & Gim, 2014). TAM continues to be the most often used model for examining technology adoption and use. Thirdly, although it is widely used in studies on technology adoption, its application to mobile learning in Saudi institutions is still restricted. This highlights the necessity of strengthening its explanatory power in this developing context. The Figure 1 illustrates the research design for this study, which integrates constructs like PU, PEOU, perceived knowledge, engagement and motivation to examine their inclusion impact on the acceptance and adoption of IA tools in learning English language.

Figure 1 :Hypothesised model of the research

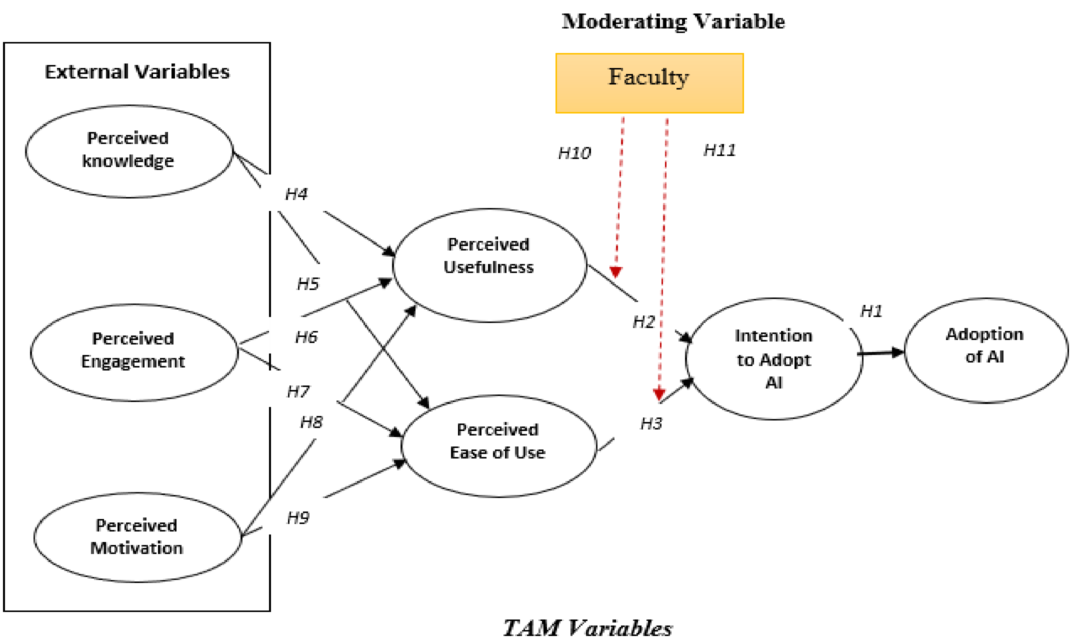

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Figure 2 Saudi EFL students' conceptual framework

Literature Review and Hypothesis Development

TAM Main Constructs

According to Fishbein and Ajzen's 1975 theory of reasoned action, intentional acts motivated by behavioural intention are what lead to human behaviours. People's knowledge or opinions regarding the behaviour in question influence this aim. TAM, which was developed to predict users' behavioural intentions and subsequent behaviours, is based on this notion. TAM has emerged as a prominent framework for understanding the acceptance of e-learning systems, renowned for its robustness, reliability, and efficacy (Sumak et al., 2011; Venkatesh & Davis, 2000; yan, & Papagiannidis, 2023; Diop, et al., 2019). According to TAM, PU and PEoU influence people's attitudes towards technology. PU signifies an individual's perception of the extent to which technology can enhance their performance, while PEU gauges an individual's belief in their ability to use technology effortlessly and with minimal exertion (Davis, 1989; Herlina et al., 2023). BI denotes an individual's intention to employ technology. Through influencing PU, which in turn forecasts actual usage, PEoU influences behavioral intention (Davis, 1989). TAM's inherent simplicity allows for seamless extension and adaptation without introducing complexity to its foundational structure (Venkatesh et al., 2003; Musa et al., 2024; Alharbi, 2024). Previous empirical evidence concerning the adoption of various technologies (Lederer, et al., 2000; Huang & Liaw, 2018; Sun & Gao, 2019) lends credence to these constructs. Building upon this theoretical foundation, the following hypotheses are posited:

H1: Saudi EFL university students' behavioural intention predicts their actual adoption of AI tools in the English learning.

H2: Saudi EFL university students' PU positively predicts their intention to adopt AI tools in their English learning.

H3: Saudi EFL university students' PEoU positively predicts their intention to adopt AI tools in their English learning.

Conceptual Framework External Constructs

Perceived Knowledge

Knowledge is crucial in behavior change. For over three decades, scholars have studied how an individual's knowledge affects behavior. It significantly influences decision-making and the search for relevant information (Raju, Lonial, & Mangold, 1995; Philippe & Ngobo, 1999; Bouzaabia & Salem, 2010). Perceived knowledge positively PU and PEoU in various contexts. Research on students' perception of Instagram for writing practice found that students' knowledge of Instagram was advantageous for its use (Mardiyanah et al., 2022). Additionally, a study on online learning showed that PU and PEoU positively influenced student satisfaction and attitude (Nurvakin et al., 2023). Moreover, a study on MOOCs highlighted that PU and PEoU significantly impacted students' intention to use MOOCs (Ibrahim, 2023). Furthermore, a study on consumer loyalty in the computer industry demonstrated that PU and PEoU had a positive impact on customer satisfaction and trust, ultimately leading to customer loyalty (Wilson et al., 2021). These findings collectively suggest that perceived knowledge plays a crucial role in shaping the PU and PEoU in various technological and educational settings.

H4: Saudi EFL university students' knowledge of AI tools positively predicts PU of AI tool in learning English.

H5: Saudi EFL university students' knowledge of AI tools positively predicts their PEoU of AI tool in learning English.

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Learning Engagement

Engagement refers to the level of active involvement and interest learners show in language learning activities (Hiver et al., 2024). It involves attention and deep cognitive processing, which enhances information retention. Meaningful learning requires engaged learners who actively participate, explore topics thoroughly, and seek learning opportunities. Thus, promoting engagement is a key focus in educational research and practice to improve language learning outcomes. Learners' engagement plays a crucial role in shaping their perceptions of the usefulness and ease of use of AI tools in language learning. Studies on various AI tools like QuillBot (Syahnaz & Fithriani, 2023), Duolingo (Listiana, et al., 2023), and AI apps (Toar, et al., 2022) highlight that students exhibit positive attitudes and enjoyment when engaging with these tools, leading to favorable perceptions of their utility and ease of use. Additionally, research on automatic written evaluation (AWE) tools Frauenfeld. (2022) emphasizes the importance of learner engagement in the feedback process to enhance writing accuracy and ability. Furthermore, incorporating AI-related activities in learning models can increase student engagement, self-direction, problem-solving skills, and participation, ultimately confirming the usefulness of AI tools in language learning (Shin, 2021). Therefore, active engagement of EFL learners with AI tools positively influences their PU and PEoU in language learning contexts.

H6: Saudi EFL university students' engagement positively predicts their PU of AI tool in learning English.

H7: Saudi EFL university students' engagement positively predicts their PEoU of AI tool in learning English.

Learners' Motivation

Motivation is the underlying reason for intentional behavior (Lai, 2011). It drives individuals to achieve goals by energizing their efforts and guiding their actions. In language learning, motivation is essential for effective and sustained learning. Motivated learners exhibit commitment through their behavior, emotions, and cognitive involvement, and are characterized by optimism, persistence, cooperation, and a desire to acquire new knowledge (Ormrod, 2010; Gass et al., 2020). The relationship between EFL learners' motivation and their PU and PEoU is crucial in language learning. Studies have shown that motivation plays a significant role in enhancing PU and PEoU in language learning contexts (Ameen et al., 2022; Tsai, 2014). Specifically, intrinsic motivation, such as intrinsic interest in the language and culture, has been highlighted as a key factor in improving learning outcomes and psychological development in EFL students (Peng, 2021). Additionally, the implementation of technology, like a Blackboard course management system, has been found to positively influence PU and PEoU, leading to improved writing performance in English courses (Braida, 2022). Therefore, fostering intrinsic motivation and integrating technology effectively can enhance EFL learners' PU and PEoU of language learning tools and materials.

H8: Saudi EFL university students' motivation predicts their PU of AI tool in learning English.

H9: Saudi EFL university students' motivation positively predicts their PEoU of AI tool in learning English.

Research Methodology

Research Design and Instrument

In line with the nature of its objectives, this study employed a cross-sectional design to collect data using a quantitative approach. A systematic questionnaire with four demographic items and 35 items divided into seven variables was used. The questionnaire items were taken from previous studies and appropriately modified to fit the technology and domain that were being examined.

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Motivation was assessed using six items developed based on previous studies (Chen & Zhao, 2022; Ryan & Deci, 2027; Ali & Bin-Hady, 2019, Alharbi, 2024) An example item reads: "AI tools make me more motivated to learn English."

To assess Engagement, four items from Abbasi et al. (2013) were employed, including a sample item like "AI tools keep me engaged in learning languages." Perceived knowledge was evaluated using five items adapted from different previous studies (Flynn & Goldsmith, 1999; Zubair et al., 2020) with a sample item reading "I know about different AI tools for learning languages." Five questions that were modified from Davis (1989) Alharbi (2024) were used to measure PU. An example item from the list was "AI tools are helpful in improving my language skills." Five items from Davis (1989) Alharbi (2024) were used to measure PEoU. Examples of these things are "AI tools are easy to use for language learning." Five items that were modified from Davis (1989) and Alharbi (2024) were used to evaluate learners' intentions to use AI tools. An example item from the assessment was "I intend to use AI tool to enhance my language learning in the near future." Five items from David (1989) Alharbi, 2024 were used to measure the real utilization of AI tools. Sample items included "I consistently use AI tools for language learning."

The survey employed a five-point Likert scale, asking respondents to rate how often or to what extent they agreed with each item that best described their usage, intention to use, and perception. Academic researchers from different universities as well as professors of English education were consulted to determine the measurement items' face validity. Each item's length and clarity were evaluated by them.

In addition, a validation template containing all the questions and items was provided to five education professionals to validate the questionnaire. These specialists were responsible for confirming that the survey's questions are in line with the main variables operational definition and providing comments on the validity of the question. Lastly, Cronbach's alpha was utilized to evaluate the study internal reliability for each of the five constructs.

Survey Respondents

727 This study was conducted at King Saud University (KSU), a prominent public research institution situated in Riyadh, the capital city of Saudi Arabia. KSU has a substantial student population of approximately 61,412 individuals enrolled in 2023, rendering it the largest university in the country. Renowned for its academic offerings and strategic urban location, KSU attracts students from diverse regions nationwide. Given the convergence of students from various governorates to the capital, the study's sample somewhat reflects the broader student populace across the nation.

The research sample encompassed 472 Saudi EFL students from two faculties within KSU: Languages and Translation (N = 283) and Arts (N = 189), comprising both male and female students aged between 20 to 24 years. These students spanned different academic levels, including 127 sophomores, 111 juniors, 90 seniors, and a remainder of freshmen. Simple random sampling was employed as the sampling technique.

The researchers compiled a list of Saudi EFL students from the faculties' databases to establish the sampling frame. The study sample size was then obtained by choosing matriculation numbers at random from this frame. According to Kline (2023), the study's research objectives were met, and structural equation modeling (SEM) was made possible with a sample size of 472 participants. Every student whose number was picked was given the questionnaire, guaranteeing equal representation from the two faculties.

Data Analysis

Version 29 of SPSS was used for descriptive analysis and data screening, and AMOS 29.0 was used for structural equation modelling (SEM). The first measurement model was estimated to ensure the study hypothesized model reliability, convergent and divergent validity of the models in accordance with accepted practices (Hair et al., 2017; Kline, 2023). The hypotheses assessed in the next step utilising AMOS version 29's structural model (Kline, 2023), while multiple-group analysis (MGA) was employed to test the moderation effect of faculty.

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Results

Estimation of the Saudi EFL University Students' Measurement Model

To evaluate the model's psychometric properties, seven measurement models of TAM main variables and the three external variables., perceived knowledge, learning engagement, learning motivation were tested by using confirmatory factor analysis (CFA). This measurement model of Saudi EFL university students consists of 35 items measuring the seven variables with 5 items for each variable. However, due to low loadings (BI1, AU4, PU1, PK3, PE4, PE5, PM3 and PeoU2) were eliminated after multiple iterations to improve the measurement model. Following these modifications, the final revise measurement model (Figure 2) produced results that were satisfactory. With a chi-square (X2) value of 893.772, degrees of freedom (df) = 303 and a p-value of 0.000, the overall fit of the model was shown to be robust. Furthermore, Kline (2023) reported that the Root Mean Square Error of Approximation (RMSEA) was.064, significantly less than the permissible criterion of.08. Additionally, the Tucker-Lewis Index (TLI) was.942, and the Comparative Fit Index (CFI) recorded.950, both above the suggested threshold of.90. Hence, an excellent goodness of fit for the Saudi EFL university students' measurement model based on Kline (2023) recommendations (see Figure 2).

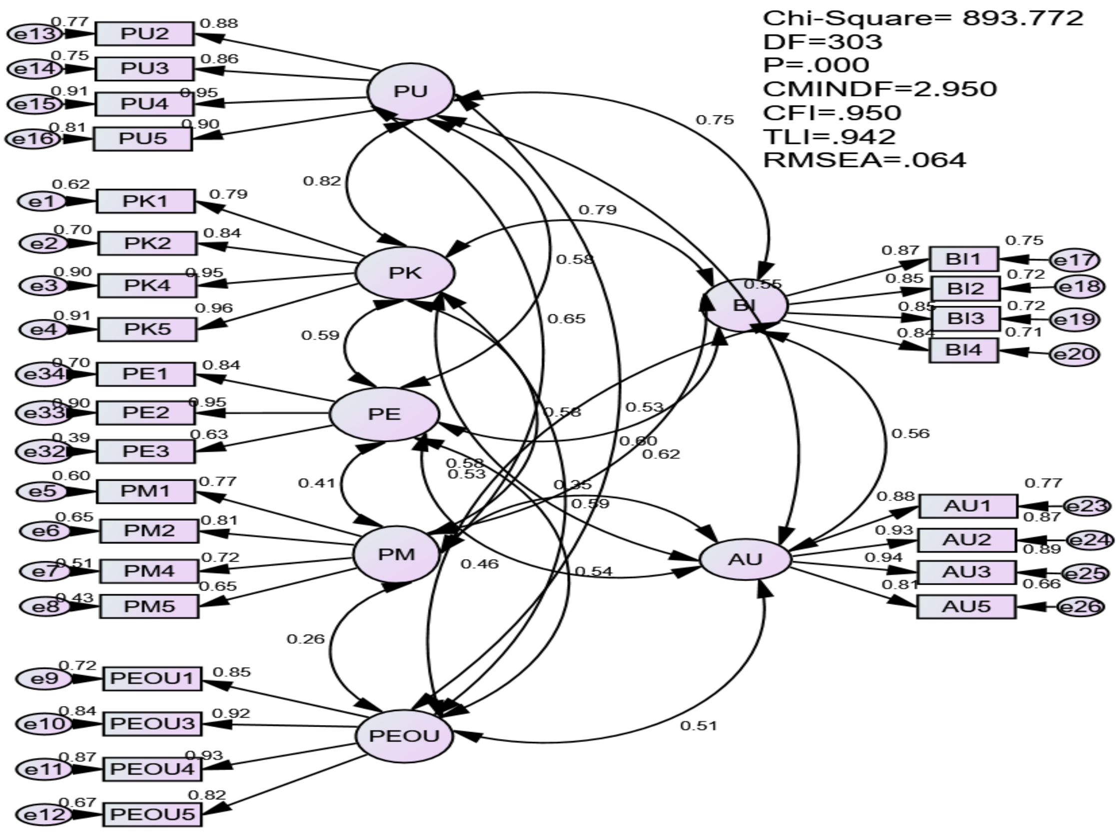

Figure 2: *Measurement Model for Saudi EFL university students*

The estimation of its convergent validity of the current study model was confirmed through the values of the average variance extracted (AVE) which were above the cut-off score of <0.05 (Hair et al., 2017; Kline, 2013). Meanwhile the reliability of this model the was ensured through the values of the composite reliability all of which are over the predetermined threshold of 0.70 (Hair et al., 2017; Kline, 2013). Hence, the results

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of the measurement constructs' convergent validity and reliability for Saudi EFL university students showed satisfactory values (see Table).

Table 1: *A summary of the measurement constructs' convergent validity and reliability for Saudi EFL university students*

Construct	Item	Factor loadings	S.E.	C.R.	P	CR	AVE
Motivation	PM1	.775				0.828	0.547
	PM2	.805	.065	16.864	***		
	PM4	.717	.067	15.083	***		
	PM5	.652	.063	13.652	***		
Perceived Ease of Use	PEOU1	.868				0.934	0.780
	PEOU4	.919	.040	27.893	***		
	PEOU3	.922	.028	37.088	***		
	PEOU5	.819	.032	26.706	***		
Perceived Usefulness	PU2	.879				0.944	0.809
	PU4	.953	.033	32.968	***		
	PU3	.865	.037	26.500	***		
	PU5	.899	.039	28.805	***		
Behavioural Intention	BI1	.869				0.915	0.728
	BI2	.850	.037	24.188	***		
	BI3	.850	.044	24.219	***		
	BI4	.844	.042	23.896	***		
Perceived Knowledge	PK4	.924					
	PK2	.844	.031	29.133	***		
	PK1	.845				0.940	0.797
	PK5	.952	.025	43.476	***		
Actual Adoption	AU1	.881				0.961	0.803
	AU2	.927	.035	31.443	***		
	AU3	.929	.034	31.564	***		
	AU5	.827	.040	24.497	***		
Learning Engagement	PE1	.836				0.852	0.664
	PE3	.627	.053	14.757	***		
	PE2	.949	.049	22.934	***		

In the same vein, the estimation of the divergent validity of the Saudi EFL university students'measurement model was assessed via the Fornell Larcker criterion (1981) criteria. According to this criterion, to ensure the divergent validity of the model, the constructs' square roots of the AVE should be greater than the squared correlation estimations of the other constructs' values. In this study as shown in Table 2, none of the inter-factor correlations are higher than square roots of the AVE which is in line with Fornell-Larcker criteria and provide strong support for the divergent validity of this study model.

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Table 2: *Model's divergent validity according to the FLC analysis for Saudi EFL university students*

Variables	PEOU	PU	BI	AU	PK	PM	PE
PEoU	**0.883**						
PU	0.525	**0.900**					
BI	0.524	0.749	**0.853**				
AU	0.506	0.542	0.573	**0.896**			
PK	0.588	0.820	0.797	0.579	**0.893**		
PM	0.259	0.652	0.620	0.347	0.588	**0.740**	
PE	0.540	0.579	0.602	0.461	0.589	0.407	**0.815**

Note: In bold are the square root of average variance extracted (AVE) and blew them are the square of correlation of the constructs.

Estimation of the Saudi EFL University Students' Hypothesized Structural Model

After estimation the measurement model psychometric properties, the model was converted into a structural model by inserting hypothetical causal paths in place of dimension correlations. In accordance with recommendations by Kline (2023 and Byrne (2013) to draw the required covariance between the variable of the study model, only the exogenous constructs, i.e., knowledge, engagement and motivation were permitted to preserve correlations.

Based on 311 degrees of freedom, the findings showed a chi-square value of 1038.214, a Tucker-Lewis index (TLI) of.931, a comparative fit index (CFI) of.939, and a CMIN/df ratio of 3.338. These indexes are all in line with the acceptable cutoff point >0.90. Furthermore, the 0.070 root mean square error of approximation (RMSEA) value was within the permissible range of <0.08. Together, these results demonstrated a high degree of consistency with the hypothesised model, confirming that the structural model, in line with Kline (2023), provided a good fit for the data (see Figure 3).

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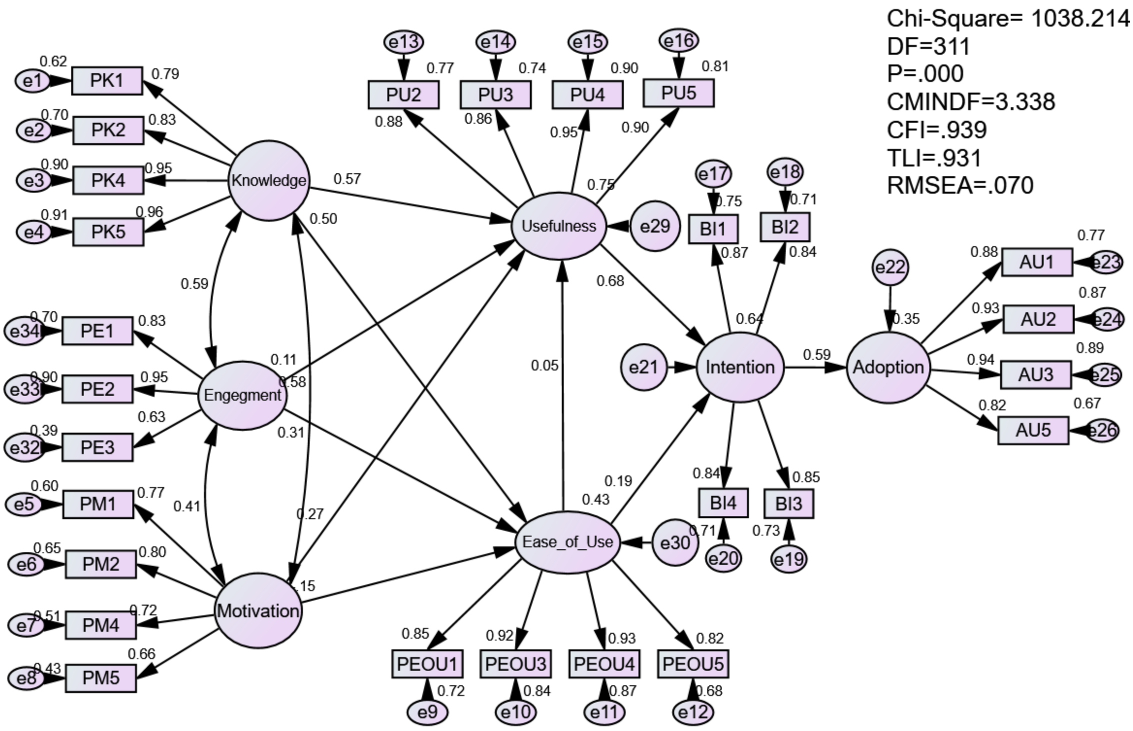

Figure 3: *Structural Model* for Saudi EFL university students

As shown in Table 3, the results of the direct hypothesized relationships between the variables were all supported. Based on the determination coefficient (R2) value of the endogenous variables, i.e., PU, PEoU of use, intention to adopt AI in English learning and actual adoption of AI among Saudi university EFL students of were explained the external variables (perceived knowledge, engagement and motivation) with 35%, 43%, 65% and 36% respectively.

Regarding the direct hypotheses, the results in Table 5 shows that Saudi EFL university students' behavioral intention predict their actual adoption of AI tools in the English learning (β = .597, $p < 0.05$). Which confirms the acceptance of the first hypothesis of the study model. In turn, their PU (β = .681, $p < 0.05$) and PeoU (β = .191, $p < 0.05$) statistically and positively predicts their intention to adopt AI tools in their English learning. Hence, both the second and their hypotheses of this study model were supported too.

Moreover, Figure 3 unveils that perceived knowledge, engagement, and motivation foster the positive perception of usefulness (β = .573, $p < 0.05$), (β = .115, $p < 0.05$), and (β = .268, $p < 0.05$), respectively. In a parallel manner, perceived knowledge, engagement, and motivation also positively impact ease of use (β = .503, $p < 0.05$), (β = .313, $p < 0.05$), and (β = .155, $p < 0.05$), respectively.

As a result, the model substantiates all nine hypotheses put forth in this study, corroborating the hypothesised relationships between the variables.

Table 3: Summary of the direct hypotheses for Saudi EFL university students

Structural Path		□□ (>.2)	C.R (>.196)	P-value	Decision
H1	BI → AU	.597	13.175	0.000	supported

H2	PU → BI	.681	14.976	0.000	supported
H3	PEOU → BI	.191	4.802	0.000	supported
H4	PK → PU	.573	12.010	0.000	supported
H5	PK → PEOU	.503	8.765	0.000	supported
H6	PE → PU	.115	3.043	.002	supported
H7	PE → PEOU	.313	6.191	0.000	supported
H8	PM → PU	.268	6.646	0.000	supported
H9	PM → PEOU	-.155	-2.902	.004	supported

Moderation Analysis of Faculty

A simultaneous analysis was conducted to test the invariance of students' faculty between two groups of Saudi EFL students from faculty of languages and translation (N = 283) and arts (N = 189). The initial analysis was performed without constraining the path coefficients (PU/PEoU → Intention to adopt AI tools), yielding a baseline chi-square value. In the subsequent analysis, the path coefficient (PU/PEoU → Intention to adopt AI tools) was constrained to be equal across both faculty groups.

The results indicated that the chi-square value (1.86) was lower than the critical chi-square value (3.84) at $p < 0.01$. This finding suggests that there is no significant difference in the hypothesized model between students from the Faculty of Languages and Translation and the Faculty of Arts among Saudi EFL students. Consequently, the faculty does not moderate the relationship between PU and the intention to adopt AI tools in learning English.

Similarly, the analysis of the relationship between perceived ease of use and the intention to adopt AI tools among Saudi EFL university students revealed a chi-square value (2.39), which was also lower than the critical chi-square value (3.84) at $p < 0.01$. This indicates that there is no significant difference in the hypothesized model between students from the Faculty of Languages and Translation and the Faculty of Arts among Saudi EFL students. Therefore, the faculty does not moderate the relationship between perceived ease of use and the intention to adopt AI tools in learning English.

Table 6 Structural Invariance Analysis of Student' Faculty

Path	Mode	Chi-squared	df	Critical Value	Chi-squared Change	Result
PU → IA	Unconstrained	1191.887	324	3.84	1.86	Not Significant
	Constrained	1196.286	325			
PEoU → IA	Unconstrained	1191.887	324	3.84	2.39	Not Significant
	Constrained	2421.653	325			

Discussion and Implications

To develop a nuanced understanding of technology acceptance, this study leverages an extended Technology Acceptance Model (TAM) that integrates three external factors: perceived knowledge, learners' engagement, and learning motivation. This enhanced TAM model goes beyond the traditional framework by offering deeper insights into the cognitive processes that drive behavioral choices. The primary aim of this research is to identify the determinants that influence Saudi EFL (English as a Foreign Language) university students to adopt AI tools and to examine their intentions and actual adoption behaviors in the context of language learning.

The extended TAM model was rigorously validated through Structural Equation Modeling (SEM), with the analysis showing robust support for the data. The results demonstrate that the additional factors—perceived knowledge, learners' engagement, and learning motivation—significantly impact students' perceptions of the usefulness and ease of use of learning tools. These perceptions, in turn, affect their behavioral intentions to adopt AI tools in language learning. The external variables accounted for 35%, 43%, 65%, and 36% of the variance in PU, PEoU, intention to adopt AI, and actual adoption of AI among Saudi university EFL students, respectively. Thus, the study's objectives were met, and the expanded TAM model provided a comprehensive elucidation of the factors motivating Saudi EFL university students to utilize AI tools in their educational endeavors.

The research specifically explored the relationship between Saudi EFL university students' intentions to adopt AI tools and their actual adoption behaviors. Testing Hypothesis 1 revealed a significant correlation between students' intention to adopt AI tools and their eventual adoption behaviors, aligning with empirical evidence from similar studies on technology adoption (Huang & Liaw, 2018; Sun & Gao, 2019). The study also examined the influence of three external factors—perceived knowledge, learners' engagement, and learning motivation—on students' use of AI tools in language learning. These factors were introduced as external variables in the TAM, thus broadening its scope.

Both Hypotheses 4 and 5, which investigated the relationship between students' perceived knowledge and their perceptions of usefulness and ease of use, were found to be statistically significant. This is consistent with previous research (Mardiyanah et al., 2022; Nurvakin et al., 2023; Ibrahim, 2023; Wilson et al., 2021), highlighting the role of perceived knowledge in influencing students' PU and PEoU of AI tools. Hypotheses 7 and 8 focused on the impact of learning engagement on students' PU and PEoU, both showing significant associations. These findings resonate with existing literature on AI tools and technology acceptance (Shin, 2021; Syahnaz & Fithriani, 2023; Listiana et al., 2023; Toar et al., 2022), emphasizing the importance of engagement in shaping students' perceptions of AI tools.

Similarly, Hypotheses 9 and 10, which explored the impact of motivation on students' PU and PEoU, yielded statistically significant results. These outcomes align with empirical studies (Ameen et al., 2022; Tsai, 2014; Peng, 2021; Braida, 2022) that underscore the influence of motivation on students' perceptions of the usefulness and ease of use of AI tools.

This work has practical, methodological, and theoretical implications. From a theoretical standpoint, the study adds to the body of literature by extending the Technology Acceptance Model to incorporate learners' engagement, perceived knowledge, and learning motivation as extra factors influencing the adoption of AI among Saudi EFL university students. The basic TAM characteristics of PU and PEoU are reinforced by this enlarged model, which also improves its predictive ability in analyzing AI adoption patterns in non-Western contexts.

Methodologically, this study validates the extended TAM model in a Middle Eastern setting, confirming its applicability and relevance beyond Western cultural contexts. This suggests that the extended TAM can effectively explain technology acceptance behaviors in diverse cultural environments, challenging the notion that TAM frameworks are inherently Western-centric.

Practically, this research highlights the limitations of the original TAM by demonstrating how the integration of perceived knowledge, engagement, and motivation can provide a more comprehensive understanding of the factors influencing AI tool adoption. These findings have significant implications for future research and practice, particularly in enhancing the adoption of AI tools in educational settings.

Furthermore, the study provides insightful information about how Saudi EFL students at King Saud University are now adopting AI tools. The benefits of incorporating AI tools into conventional educational frameworks can be better understood by educators and policymakers, such as the Ministry of Higher Education, based on these findings. This groundbreaking study adds to the body of knowledge on language learning and teaching, especially as it relates to Saudi universities, by offering actual data on the adoption and application of AI tools.

Conclusions and Limitations

In essence, this study provides a critical and comprehensive examination of the factors driving the adoption of AI tools among Saudi EFL university students. It extends the TAM framework and offers practical insights that can guide the integration of AI in educational practices, thereby expanding the knowledge base in the field of language learning and technology adoption. The analysis reveals that students' perceptions of the usefulness and ease of use of AI tools significantly affect their intention to integrate these technologies into their learning processes. Additionally, the incorporation of perceived knowledge, learner engagement, and learning motivation into the Technology Acceptance Model (TAM) enhances the understanding of these influences on the mediating variables— PU and PEoU. This research critically examines the applicability of an extended TAM framework in the context of a developing country with a non-Western culture, thereby challenging the predominant view that TAM theories are biased towards developed nations.

However, the study is not without limitations. Firstly, its scope is confined to factors pertinent to the adoption of AI tools by Saudi EFL university students. Due to time and financial constraints, the research did not consider other potentially significant factors such as student anxiety, social influence, privacy concerns, and institutional support. Secondly, the findings are specific to Saudi EFL university students and do not generalize to EFL students at the pre-university level or to university students in different academic disciplines. This limitation stems from the researcher's strategic focus on a particular demographic. Thirdly, the study sample is restricted to a single institution, King Saud University, and exclusively includes Saudi EFL students. As a result, caution is warranted when generalizing these findings to other universities in Saudi Arabia. This sample limitation was influenced by logistical challenges, particularly the ongoing conflict in certain regions, which impeded the ability to gather a broader sample from multiple universities across the country. These constraints highlight the need for future research to broaden the scope and diversity of samples and to explore additional variables that could impact the adoption of AI tools in educational settings.

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