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Predicting EFL Students' Use of Artificial Intelligence Tool in Advancing Their Writing Skills

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Abstract

This study examines the factors influencing the adoption and use of artificial intelligence (AI) tools to enhance writing skills among English as a Foreign Language (EFL) learners in Oman, guided by the Unified Theory of Acceptance and Use of Technology (UTAUT). The objectives were to assess the impact of performance expectancy, effort expectancy, social influence, and facilitating conditions on students' behavioral intention and actual AI usage, and to test the moderating role of prior AI experience. A cross-sectional quantitative design was employed, with data collected from 255 undergraduate female EFL students through a validated questionnaire. Structural equation modeling (SEM) and confirmatory factor analysis were used to validate the measurement model and test hypothesized relationships. Findings indicate that behavioral intention and facilitating conditions significantly predicted actual AI tool use, while performance expectancy, effort expectancy, and social influence strongly shaped behavioral intention. Mediation tests confirmed that behavioral intention served as a key pathway linking UTAUT constructs to actual adoption, and moderation analysis showed that prior AI experience strengthened the intention–usage relationship. This research contributes to a context-specific, evidence-based framework for AI adoption in EFL writing, offering novel insights for educators, institutions, and technology designers to integrate AI ethically and effectively in language learning.

Keywords:

UTAUT; Framework;
AI in Education;
EFL Learners;
Writing Enhancement;
Adoption Factors; AI Usage;
Educational Technology.

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1- Introduction

The rapid advancement of artificial intelligence (AI) has significantly reshaped language education, particularly in enhancing the writing skills of English as a Foreign Language (EFL) learners. Studies increasingly report that tools such as ChatGPT, Grammarly, and Automated Writing Evaluation (AWE) platforms not only provide immediate feedback but also improve grammatical accuracy, coherence, and overall writing fluency [1, 2]. Despite these benefits, learners show different patterns of adoption shaped by their perceptions of usefulness, ease of use, peer expectations, and the degree of institutional support [3]. At the same time, concerns persist about over-reliance on automation, reduced critical thinking, and ethical challenges such as plagiarism, authorship attribution, and data privacy [4, 5].

To better understand these dynamics, the current study employs the Unified Theory of Acceptance and Use of Technology (UTAUT) as a comprehensive framework for analyzing technology adoption in education, focusing on performance expectancy, effort expectancy, social influence, and facilitating conditions [6]. Prior research confirms that AI-based writing support can enhance motivation, revision practices, and overall achievement [7], yet also warns that excessive reliance may stifle creativity and weaken engagement in the writing process [4, 8]. In addition, questions of academic integrity, authorship responsibility, and ethical deployment are increasingly discussed in the literature but remain insufficiently integrated into empirical adoption models [8].

However, significant gaps remain in existing scholarship. First, although UTAUT has been widely applied to e-learning and educational technology [9-12], its application to AI-driven writing tools in language education remains limited. Second, most studies have been conducted in Western and Asian contexts, with Middle Eastern settings

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underexplored, despite their distinct cultural, institutional, and infrastructural characteristics [3, 13]. Third, facilitating conditions such as institutional readiness, training, and technical support are often assumed to enable adoption but lack rigorous empirical validation [14]. Finally, the role of prior AI experience in strengthening the relationship between intention and actual adoption is rarely examined [15-17].

This research addresses these gaps by applying the UTAUT framework to investigate Omani EFL learners' acceptance and use of AI-powered writing tools. Specifically, it examines the mediating role of behavioral intention, the direct and indirect effects of facilitating conditions, and the moderating effect of prior AI experience. By doing so, the study contributes a contextually grounded and evidence-based framework for AI adoption in EFL writing, offering novel insights for educators, institutions, and policymakers on how to integrate AI tools effectively and ethically in language learning. The remainder of this article is organized as follows: Section 2 develops the conceptual framework and hypotheses; Section 3 outlines the methodology; Section 4 presents the results; Section 5 discusses the findings in relation to existing literature; and Section 6 concludes with implications, limitations, and recommendations for future research.

2- Conceptual Framework and Hypothesis Formulation

2-1- Theoretical Foundation

The Unified Theory of Acceptance and Use of Technology (UTAUT) provides a comprehensive framework for analyzing user behavior in relation to technology adoption. It integrates key constructs from several foundational models, including the Theory of Reasoned Action (TRA), the Technology Acceptance Model (TAM), and Social Cognitive Theory. According to Venkatesh et al. (2003) [6], four primary variables—performance expectancy, effort expectancy, social influence, and facilitating conditions—collectively shape individuals' intentions to adopt technology as well as their actual usage patterns. Over the past two decades, UTAUT has been widely validated across domains such as e-learning, mobile learning, healthcare, and workplace innovation, establishing its strength in explaining adoption behavior [18-25].

In educational technology research, UTAUT is particularly valuable because it accounts for both individual cognitive perceptions (e.g., usefulness and ease of use) and contextual enablers (e.g., peer influence and institutional support). This dual focus makes it highly relevant for studying AI in language learning, where adoption depends not only on perceived utility but also on the surrounding academic culture and infrastructure. Furthermore, UTAUT's emphasis on behavioral intention as a mediator aligns with pedagogical contexts in which students' willingness to adopt new tools is often a prerequisite for meaningful usage.

Building on this theoretical foundation, the current research applies the UTAUT model to investigate the factors that affect EFL learners' use of AI-powered writing tools. The proposed framework, presented in Figure 1, assesses how the four core predictors contribute to students' intention to engage with AI technology and their actual behavior in using it. This study also extends the model by incorporating prior exposure to AI tools as a moderating factor, addressing calls in recent literature to consider learners' digital experience when explaining technology adoption. By situating UTAUT within the context of EFL writing, this research advances the theoretical application of the model beyond general e-learning to the more specialized domain of AI-supported language education, thereby providing both theoretical refinement and practical insight.

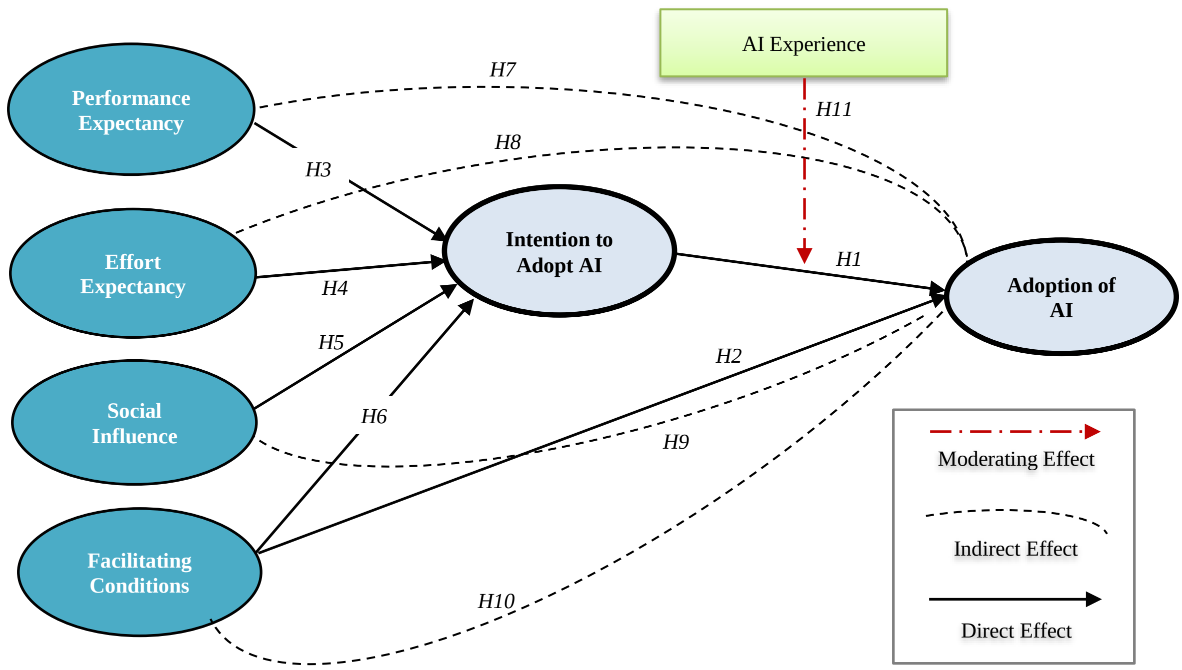


Figure 1. Hypothesised model of the research

2-2- Hypotheses Development

2-2-1-Factors Influencing AI Adoption in EFL Writing Advancement

The transition from learners' intention to actual implementation of AI-based writing tools within EFL contexts is shaped by both environmental supports and internal motivational drivers. External factors, including institutional readiness, access to technological infrastructure, and the provision of training opportunities, are essential in supporting the adoption of AI-enhanced writing tools [14]. Research in the field of educational technology emphasizes that when universities actively promote AI readiness through structured instructional programs and accessible technological resources, learners are more likely to progress from mere intention to sustained usage [15, 26].

At the same time, behavioural intention continues to serve as a primary motivational determinant in the adoption process. Accumulating evidence shows that students who perceive AI tools as beneficial for enhancing writing efficiency and output quality are more inclined to integrate them into their academic routines [10, 27]. However, some concerns remain, particularly regarding the possibility that over-reliance on AI could hinder creativity or undermine academic originality [15].

Research evidence also indicates that facilitating conditions influence the strength of the link between users' intention and their actual adoption behaviours. Studies indicate that while non-academic professionals view AI tools as efficiency enhancers, academic users remain cautious due to biases, ethical concerns, and job displacement risks [14]. Similarly, research on AI-powered teacher-bots found that students with institutional support and AI literacy training were significantly more likely to transition from intention to actual adoption [10]. Based on these insights, the following hypotheses were formulated:

H1: The intention to adopt AI positively influences the actual adoption of AI tools for writing advancement.

H2: Facilitating conditions positively influence the actual adoption of AI tools for writing advancement.

2-2-2-The Role of Performance Expectancy and Effort Expectancy

Within the sphere of EFL writing development, both performance expectancy and effort expectancy emerge as key psychological constructs shaping learners' intentions to engage with AI technologies. Performance expectancy—referring to the degree to which learners perceive AI tools as beneficial for improving their writing performance—has been consistently recognized as a dominant factor in influencing adoption. When students believe that AI can enhance the quality, efficiency, and overall productivity of their writing, they tend to exhibit a greater willingness to adopt such technologies [13, 28]. This effect is often intensified among users with higher levels of digital competence, as technologically proficient individuals are more likely to extract functional value from AI applications [29].

In a similar vein, effort expectancy—defined as the perceived ease associated with using AI tools—significantly informs learners' adoption choices. When AI-powered writing platforms are intuitive and require minimal cognitive or technical effort, learners demonstrate increased engagement [30]. Insights from research across educational and healthcare settings indicate that reducing complexity in user interfaces can substantially raise the likelihood of technology uptake [31, 32]. However, ease of use alone may not suffice as a predictor unless it coexists with other factors such as perceived utility, intrinsic motivation, and trust in the AI system's functionality [33] .Additionally, meta-analytical evidence points to the moderating influence of contextual variables—including geographic location, gender, and institutional support—in shaping the strength of effort expectancy's impact on adoption [13] .

Studies involving university students' use of ChatGPT reveal that while both performance and effort expectancy impact the decision to adopt AI, misalignment between these factors—for instance, perceiving AI as beneficial but difficult to operate—can hinder adoption [34]. This observation is echoed in AI-enabled decision-making research, where both constructs significantly influenced adoption patterns among professionals in healthcare environments [35]. These findings inform the development of the following hypotheses:

H4: Performance expectancy positively influences the intention to adopt AI in EFL writing advancement.

H5: Effort expectancy positively influences the intention to adopt AI in EFL writing advancement.

H6: Performance expectancy indirectly influences actual adoption through intention to adopt AI.

H7: Effort expectancy indirectly influences actual adoption through intention to adopt AI.

2-2-3-The Role of Social Influence and Facilitating Conditions

The adoption of AI in educational settings is significantly shaped by both social influence and facilitating conditions, each exerting an impact on learners' behavioural intentions. Social influence refers to the extent to which individuals feel that peers, educators, or institutional figures support or encourage the use of AI technologies; plays a pivotal role in encouraging adoption behaviours [30]. Research on AI-supported writing tools has demonstrated that students are more inclined to engage with such technologies when they observe frequent use by classmates and educators [36, 37].

In parallel, facilitating conditions—such as the availability of digital infrastructure, institutional policies, and access to relevant training—serve as key enablers of AI integration [9]. Evidence from the higher education sector suggests that both students and academic staff are more likely to adopt AI technologies when supported by institutional mechanisms that ease their implementation [9, 38]. Notably, empirical studies conducted in Saudi universities have identified facilitating conditions as the most influential factor in predicting AI adoption, thereby underscoring the need for targeted AI training initiatives and institutional support frameworks [9].

Moreover, systematic reviews on technology adoption suggest that social influence and facilitating conditions interact to establish AI tools as mainstream educational resources [39]. Research on AI-assisted writing platforms further supports this, revealing that students' perceptions of AI adoption are shaped by academic culture and institutional encouragement [40]. Drawing from these findings, the study proposes the following hypotheses:

H8: Social influence positively influences the intention to adopt AI in EFL writing advancement.

H9: Facilitating conditions positively influence the intention to adopt AI in EFL writing advancement.

H10: Social influence indirectly influences actual adoption through intention to adopt AI.

H11: Facilitating conditions indirectly influence actual adoption through intention to adopt AI.

2-2-4-Moderating Role of Leaners Artificial Intelligence Experience

Prior engagement with artificial intelligence (AI) emerges as a critical moderating variable influencing the connection between learners' intention to adopt AI and their actual usage behavior in the domain of English as a Foreign Language (EFL) writing. This research is grounded in well-known theoretical models, including the Technology Acceptance Model (TAM) [41] and the Unified Theory of Acceptance and Use of Technology (UTAUT) [6], which underscore the importance of user perceptions and contextual conditions in shaping technology adoption outcomes. Existing evidence indicates that individuals with greater familiarity with AI tools are more likely to convert their intentions into practical usage, encountering fewer psychological or operational barriers. For example, studies by Pillai et al. (2023) and Roy et al. (2022) [10, 16] users with more extensive AI exposure demonstrate stronger engagement and higher adoption efficacy.

Empirical findings in AI-enhanced EFL instruction further corroborate this moderating effect observed that learners utilizing ChatGPT-based writing platforms not only improved their writing competencies and motivation, but also benefited from prior AI experience, which appeared to ease their transition into AI-mediated learning environments [2]. Similarly, Hwang et al. (2023) [12] reported that learners with a background in AI usage showed a more seamless progression from intention to actual adoption when exposed to AI-generated feedback in authentic EFL writing scenarios. These patterns are consistent with broader technology adoption literature, such as that presented by Roy et al. (2022) [16] and Strzelecki (2023) [42], which highlight the predictive value of habitual AI use and familiarity in determining sustained engagement.

The observed moderating influence of AI experience carries practical significance for AI-integrated language education. Institutions are encouraged to design tiered AI literacy initiatives that gradually expose learners to writing technologies, thereby lowering cognitive barriers and enhancing readiness for adoption. Additionally, instructional designers and policymakers should consider the variability in prior experience when developing AI-supported curricula to ensure equitable and effective learning opportunities. Future investigations are warranted to examine the longitudinal impact of AI familiarity on long-term adoption patterns, as well as to explore how these dynamics vary across cultural and linguistic contexts. In view of these considerations, the following hypothesis is proposed:

H12: Leaners Artificial Intelligence experience moderates the relationship between intention to adopt AI and actual adoption in EFL writing advancing.

3- Research Methodology

3-1- Research Design and Instrument

To address the objectives of this study, a cross-sectional design was adopted, employing a quantitative methodology for data gathering. The main tool for data collection was a structured questionnaire comprising four demographic questions and thirty items distributed across six central constructs. These items were derived from previously validated instruments and were adjusted to align with the specific context of AI integration in English as a Foreign Language (EFL) writing instruction. The questionnaire was theoretically informed by the Unified Theory of Acceptance and Use of Technology (UTAUT) proposed by Venkatesh et al. (2003) [6], further refined based on the adaptations suggested by Hashim et al. (2018) [43]. Modifications were made to ensure contextual relevance, capturing the unique technological and pedagogical dynamics experienced by EFL learners using AI-supported writing tools. Responses were collected using a five-point Likert scale that included both agreement and frequency items, enabling the measurement of participants' perceptions, intentions, and usage behaviour with respect to AI technologies.

To ensure the instrument's validity, a panel of academic researchers from diverse universities and professors specializing in English education evaluated the questionnaire's face validity. Their feedback focused on refining item clarity, conciseness, and relevance to the study's constructs. Furthermore, a validation template encompassing all survey items was shared with five education experts to evaluate content validity. These specialists confirmed that each question corresponded to the operational definitions of the key variables and offered feedback to improve the instrument's accuracy. Finally, the study's internal reliability was rigorously examined using Cronbach's alpha, with coefficients calculated for each of the five primary constructs to confirm scale consistency. The study involved 255 female undergraduate students from the English Language program at the Faculty of Arts and Human Sciences, A'Sharqiyah University, Oman. Participants spanned multiple academic levels, with 232 first-year, 9 second-year, 4 third year, and 10 fourth-year students, offering a broad representation of learners across different stages of the program.

3-2- Data Analysis

The researcher used specialized statistical analytic software (IBM SPSS version 29.0) to perform two-phase sequential statistical analyses to ensure methodological rigor. Descriptive statistics and preliminary data screening were conducted with IBM SPSS Statistics (version 29.0) to confirm the distribution of data, identify potential outliers, and demonstrate fitness for subsequent analyses. Thereafter, IBM AMOS (version 29.0) was utilized to analyze the hypothesized links among latent constructs through standard structural equation modeling (SEM). To verify the soundness of the measurement framework, the researcher performed a confirmatory factor analysis (CFA) to examine important psychometric properties such as construct reliability, convergent validity, and discriminant validity using previously specified criteria [44, 45]. Based on the validation of the measurement model, the SEM procedures (Amos version 29.0) were performed for hypothesis testing, including the overall evaluation of the structural relationships proposed by the frameworks. Such an approach provided a systematic and rigorous means of conceptual model validation, thereby further enhancing the empirical veracity of the study.

4- Results

4-1- Descriptive Analysis for the Study Constructs

This section presents a detailed descriptive analysis of English as a Foreign Language (EFL) students' adoption patterns and intentions regarding the use of AI tools for writing development. The data were analyzed using descriptive statistics, with means and standard deviations reported for each survey item. The items were categorized into five groups reflecting the key variables under investigation. As shown in Table 1, students generally demonstrate a favourable usage pattern, evidenced by a mean score of 4.26 for the statement, "I consistently incorporate the AI tool into my writing routine." Nevertheless, the slightly lower mean of 4.20 for the item, "I actively use the AI tool for writing on a regular basis," indicates that while integration appears steady, the intensity of active engagement may be somewhat less pronounced.

Concerning behavioural intention, students express a robust commitment to continue using the AI tool, with noteworthy means such as 4.04 for "I intend to continue using the AI tool for writing in the future." Despite this enthusiasm, the more cautious stance reflected in the lower mean of 3.89 for "I have a strong intention to rely on the AI tool as a fundamental part of my writing process" signals a nuanced perspective on the tool's fundamental role.

Facilitating conditions yield generally positive perceptions, with confidence in the compatibility of the AI tool with existing writing practices and tools evidenced by a commendable mean of 3.78 for the item "The AI tool is compatible with my existing writing practices and tools." However, the slightly lower institutional support means of 3.62 for "The educational institution provides sufficient support for integrating the AI tool into the writing curriculum" points to an area for potential improvement.

Performance expectancy indicates varying degrees of optimism, with a more cautious outlook reflected in the lower mean of 2.98 for "I believe that the AI tool positively contributes to my overall writing competence." Conversely, a positive expectation is demonstrated by the mean of 3.43 for "I expect improved writing outcomes when I use the AI tool." Effort expectancy consistently highlights a positive attitude toward the ease of integrating the AI tool into writing practices. Notably, the high mean of 4.47 for "Using the AI tool for writing requires minimal mental effort on my part" reflects a perception of the tool as a convenient and mentally undemanding resource.

Social influence perceptions are generally positive, with strong endorsements from both peers and academic circles. However, the nuanced response to external pressure, as indicated by the mean of 3.95 for "I feel pressure from my social circles to incorporate the AI tool into my writing practices," suggests a more complex dynamic.

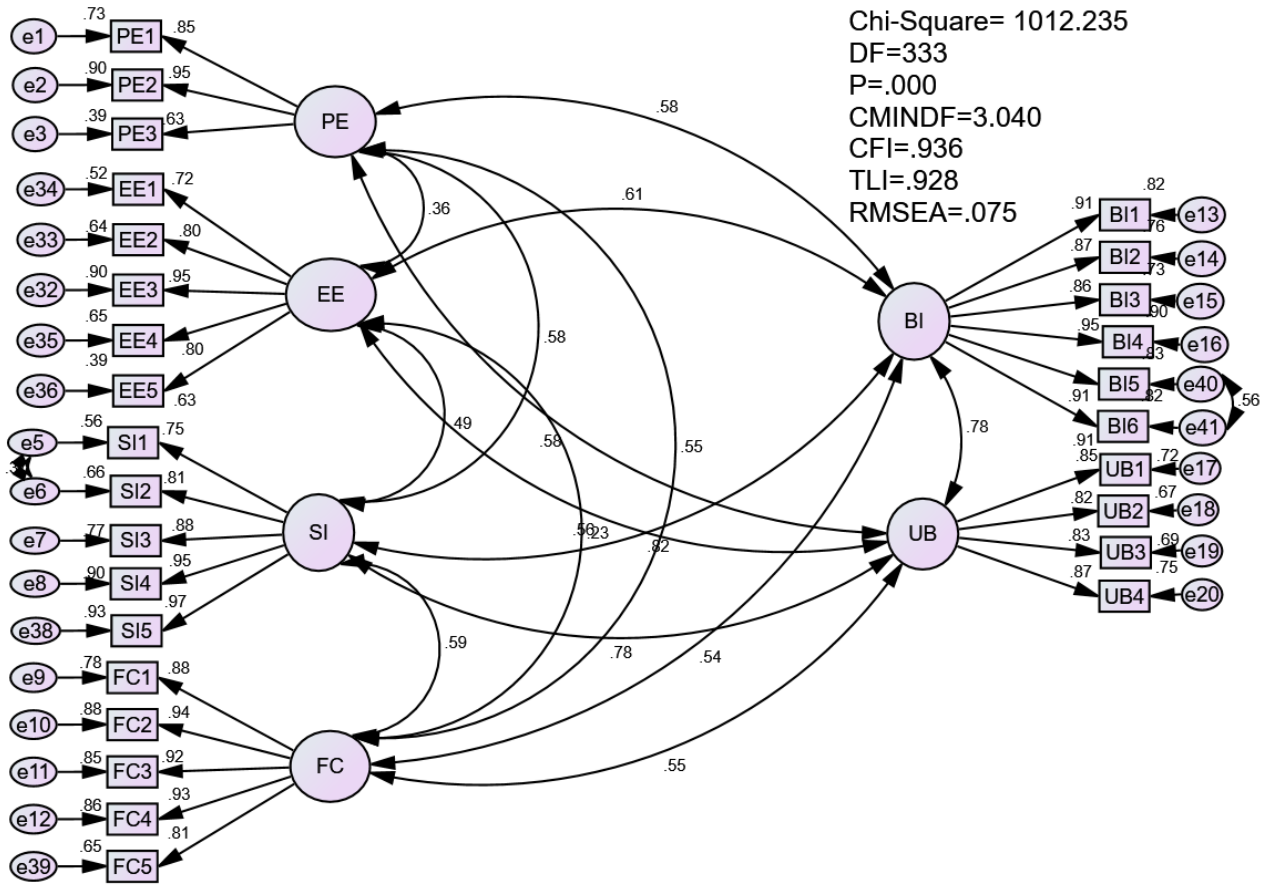
Table 1. Descriptive Statistics of Variables of Study

Constructs	Items	SD	D	N	A	SA	Mean	Std
Use Behaviour (UB):	1. I actively use the AI tool for writing on a regular basis.	2.2	5.3	13.3	28.3	50.8	4.20	1.01
	2. I consistently incorporate the AI tool into my writing routine.	1.7	2.5	15.3	29.4	51.1	4.26	.92
	3. I integrate the AI tool into different aspects of my writing assignments.	4.4	5.0	15.3	26.7	48.6	4.10	1.11
	4. My use of the AI tool has become an integral part of my overall writing process.	2.8	4.4	20.3	21.9	50.6	4.13	1.06
Behavioural Intention (BI):	1) I intend to continue using the AI tool for writing in the future.	2.8	2.2	22.2	33.6	39.2	4.04	.98
	2) I plan to recommend the use of the AI tool to my peers for improving their writing skills.	2.2	4.7	29.7	27.8	35.6	3.90	1.02
	3) I am committed to incorporating the AI tool into my long-term writing practices.	2.5	3.6	18.9	29.4	45.6	4.12	1.00
	4) I foresee myself persistently using the AI tool for various writing tasks.	2.5	4.7	23.6	27.8	41.4	4.01	1.03
	5) I have a strong intention to rely on the AI tool as a fundamental part of my writing process.	4.2	7.2	23.1	26.4	39.2	3.89	1.13
	6) I envision the AI tool becoming an essential aspect of my overall writing strategy in the coming years.	4.2	6.1	24.4	25.8	39.4	3.90	1.12
Facilitating Conditions (FC):	1. I have access to the necessary technology and resources to effectively use the AI tool for writing.	3.3	9.2	37.2	21.9	28.3	3.63	1.09
	2. The educational institution provides sufficient support for integrating the AI tool into the writing curriculum.	5.0	7.5	35.6	24.2	27.8	3.62	1.12
	3. I feel confident in my ability to use the AI tool for enhancing my writing skills.	4.4	8.3	37.2	23.6	26.4	3.59	1.10
	4. The availability of technical support positively influences my decision to use the AI tool.	5.3	9.2	36.7	24.4	24.4	3.54	1.11
	5. The AI tool is compatible with my existing writing practices and tools.	3.6	4.2	35.6	23.6	33.1	3.78	1.06
Performance Expectancy (PE):	1) I believe that using the AI tool enhances the quality of my written assignments.	11.4	11.9	38.6	18.6	19.4	3.23	1.22
	2) I expect improved writing outcomes when I use the AI tool.	9.2	8.6	35.8	22.8	23.6	3.43	1.20
	3) I perceive the AI tool as a valuable resource for achieving higher writing proficiency.	11.9	11.1	35.0	20.8	21.1	3.28	1.25
	4) I believe that the AI tool positively contributes to my overall writing competence.	20.3	16.7	27.2	16.7	19.2	2.98	1.38
Effort Expectancy (EE):	1. Using the AI tool for writing requires minimal mental effort on my part.	2.5	1.9	7.5	21.9	66.1	4.47	.90
	2. I find it easy to integrate the AI tool into my writing routine.	1.9	3.9	11.1	29.4	53.6	4.29	.95
	3. Learning to use the AI tool for writing is straightforward for me.	1.1	1.9	11.4	27.8	57.8	4.39	.85
	4. The process of incorporating the AI tool into my writing assignments is not time-consuming.	3.1	2.2	9.2	28.9	56.7	4.34	.95
	5. I feel that using the AI tool is a convenient way to enhance my writing skills.	1.7	1.7	15.3	26.7	54.7	4.31	.91
	6. Incorporating the AI tool into my writing doesn't require significant mental strain.	3.1	3.3	13.1	24.7	55.8	4.27	1.01
Social Influence (SI):	1) Using the AI tool for writing is widely accepted by influential people in my academic community.	0.6	5.0	21.7	31.9	40.8	4.08	.93
	2) My peers influence me to use the AI tool for improving my writing skills.	1.4	6.4	17.8	30.6	43.9	4.09	1.00
	3) Professors and instructors have a significant impact on my decision to use the AI tool for writing.	1.4	6.9	21.4	27.2	43.1	4.04	1.02
	4) I feel pressure from my social circles to incorporate the AI tool into my writing practices.	4.2	4.2	25.6	24.4	41.7	3.95	1.10
	5) The opinions of influential figures in the field of English language learning affect my intention to use the AI tool.	4.4	3.3	23.1	23.9	45.3	4.02	1.10

4-2- Measurement Validation

This study utilized Confirmatory Factor Analysis (CFA) to evaluate the construct validity and reliability of the measurement model. The analysis examined seven underlying latent variables—social influence, facilitating conditions, use behaviour, performance expectancy, effort expectancy, and behavioural intention—as illustrated in Figure 1. The objective was to evaluate the consistency and precision with which these constructs were operationalized within the study's sample context.

To strengthen the model's psychometric soundness, the analysis underwent several refinement stages. Items with inadequate factor loadings were closely examined, leading to the exclusion of one item each from the performance expectancy (Item 4) and effort expectancy (Item 6) constructs, due to their limited contribution to construct validity. Following these adjustments, the final model demonstrated robust statistical properties. The chi-square statistic (X^2 = 1012.235, df = 333, $p < 0.001$) indicated a statistically significant fit. The Root Mean Square Error of Approximation (RMSEA) was calculated at 0.075, which falls within the acceptable range of less than 0.08 [44]. In addition, the Comparative Fit Index (CFI) reached 0.936 and the Tucker-Lewis Index (TLI) achieved 0.928—both surpassing the minimum acceptable threshold of 0.90. These model fit indices collectively affirm that the measurement model is well-specified and exhibits a strong alignment with the empirical data, as illustrated in Figure 2.



Note: SI=Social Influence, FC=Facilitating Conditions, UB=Use Behaviour, PE=Performance Expectancy, EE=Effort Expectancy, & BI=Behavioural Intention.

Figure 2. **Study measurement model**

The evaluation of the measurement model, based on the Unified Theory of Acceptance and Use of Technology (UTAUT), aimed to predict EFL students' acceptance and use of AI-powered writing tools., demonstrated satisfactory psychometric quality. Key validity and reliability metrics—including convergent validity, discriminant validity, and composite reliability; were thoroughly analysed, affirming the model's overall integrity.

As shown in Figure 1, all standardized item loadings were above the 0.50 benchmark, signifying adequate convergent validity across the latent constructs. Furthermore, the average variance extracted (AVE) values exceeded the minimum threshold of 0.50, substantiating the construct validity of the measurement model according to established criteria. Reliability measures reinforced these findings: composite reliability (CR) values for all constructs were above the accepted cutoff of 0.70, indicating strong internal consistency [44, 45] (see Table 1).

Table 2 displays the Average Variance Extracted (AVE) values on the diagonal, serving as key indicators of discriminant validity. Above the diagonal are the squared inter-construct correlations, which represent shared variance among the factors, while the inter-factor correlation coefficients themselves are positioned below the diagonal. Critically, none of the inter-construct correlations surpass the 0.80 threshold, thereby providing empirical support for discriminant validity in accordance with widely accepted standards [45, 46]. This evidence is further reinforced by the fact that each AVE value exceeds its associated squared correlations with other constructs, demonstrating that each latent variable retains a distinct conceptual identity. These results collectively underscore the non-redundancy of the measured constructs and confirm that the instrument effectively distinguishes between the theoretical dimensions it intends to assess.

Table 2. Convergent Validity and Reliability of the Measurement Constructs

Construct	Item	Factor loadings	S.E.	C.R.	P	CR	AVE
Social Influence	SI1	0.749				0.941	0.764
	SI2	0.810	0.056	20.412	***		
	SI3	0.876	0.072	17.849	***		
	SI4	0.950	0.076	19.670	***		
	SI5	0.966	0.076	20.047	***		
Facilitating Conditions	FC3	0.922				0.953	0.803
	FC2	0.938	0.032	32.494	***		
	FC1	0.882	0.035	27.003	***		
	FC4	0.925	0.033	31.105	***		
	FC5	0.806	0.039	21.781	***		
Use Behaviour	UB1	0.846				0.906	0.706
	UB2	0.820	0.047	18.921	***		
	UB3	0.829	0.056	19.250	***		
	UB4	0.865	0.052	20.608	***		
Performance Expectancy	PE1	0.854				0.858	0.675
	PE2	0.951	0.052	21.205	***		
	PE3	0.625	0.058	13.051	***		
Effort Expectancy	EE3	0.948	0.070	17.502	***	0.889	0.620
	EE2	0.799	0.077	14.971	***		
	EE1	0.723					
	EE4	0.805	0.078	15.089	***		
	EE5	0.626	0.075	11.638	***		
Behavioural Intention	BI1	0.907				0.963	0.812
	BI4	0.948	0.034	32.033	***		
	BI3	0.856	0.040	24.342	***		
	BI2	0.874	0.039	25.554	***		
	BI5	0.910	0.041	28.385	***		
	BI6	0.908	0.041	28.203	***		

Table 3. Correlation matrix and average variance extracted

Construct	CR	AVE	BI	SI	FC	PE	UB	EE
BI	0.963	0.812	**0.901**					
SI	0.941	0.764	0.816	**0.874**				
FC	0.953	0.803	0.536	0.590	**0.896**			
PE	0.858	0.675	0.583	0.583	0.554	**0.821**		
UB	0.906	0.706	0.777	0.783	0.549	0.583	**0.840**	
EE	0.889	0.620	0.611	0.486	0.228	0.363	0.561	**0.787**

4-3- Evaluation of the Structural Model and Hypothesis Testing

Before constructing the structural model, the measurement model underwent a thorough assessment of validity and reliability to ensure the robustness of its constructs. In transitioning to the structural phase, the hypothesized directional relationships replaced inter-construct correlations, consistent with structural equation modelling practices. As recommended in methodological guidelines [44, 45], correlations were maintained only among the exogenous variables to account for potential shared variance. The evaluation of the structural model was conducted with 336 degrees of freedom, yielding a chi-square value of 1058.733 and a normed chi-square (CMIN/df) of 3.151. The model demonstrated a satisfactory fit to the observed data, as indicated by a Comparative Fit Index (CFI) of 0.932 and a Tucker-Lewis Index (TLI) of 0.924; both surpassing the conventional threshold of 0.90. Moreover, the Root Mean Square Error of Approximation (RMSEA) was calculated at 0.077, remaining within the widely accepted upper limit of 0.08. Collectively, these fit indices affirm the model's structural validity and its alignment with the underlying theoretical framework [44] (see Figure 3).

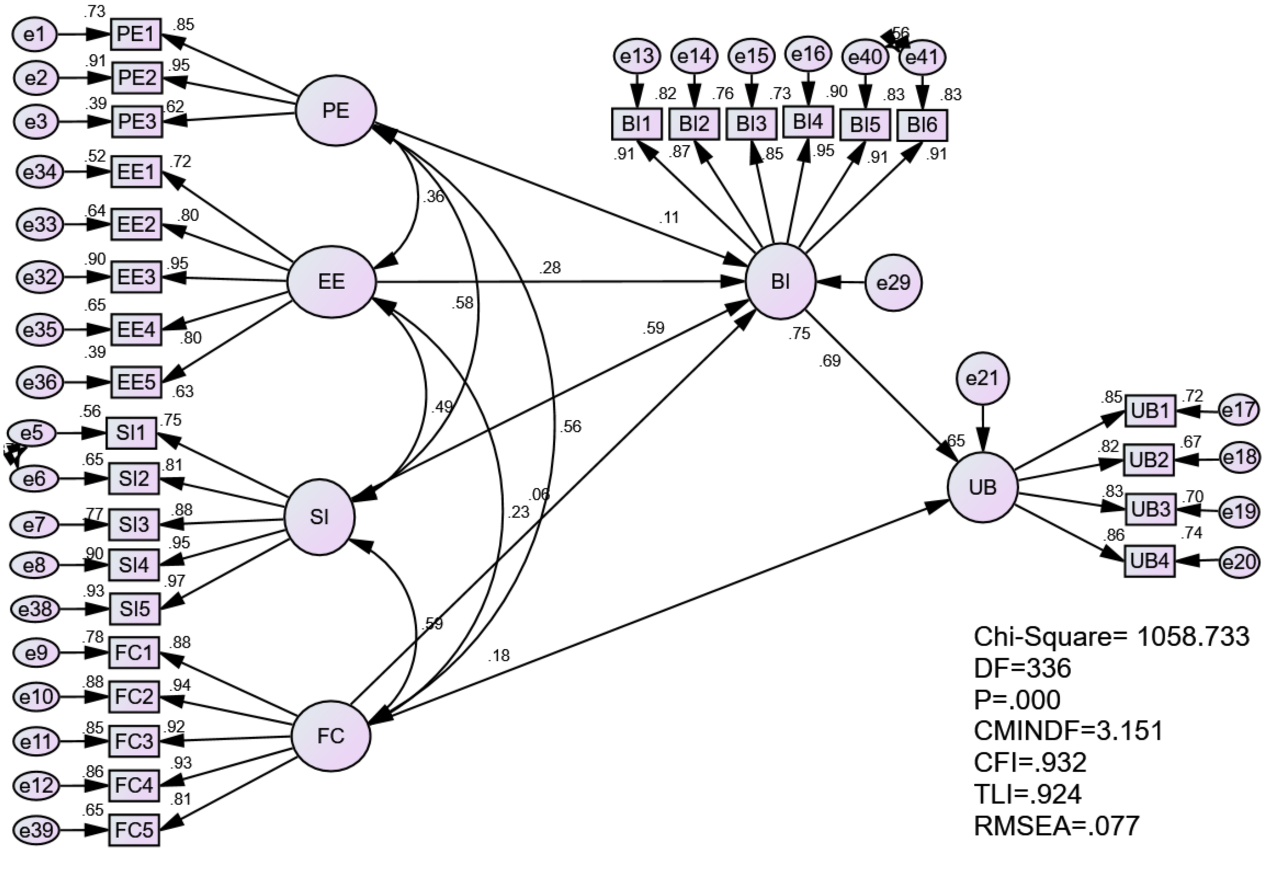


Figure 3. Study Structural Model

Figure 3 and Table 4 present the results of the structural model analysis, displaying standardized path coefficients for the hypothesized relationships. The model accounts for 65% of the variance in the adoption of AI-assisted writing tools among English as a Foreign Language (EFL) learners, grounded in the Unified Theory of Acceptance and Use of Technology (UTAUT) framework. This explanatory power is attributed to six key constructs: social influence (SI), facilitating conditions (FC), use behavior (UB), performance expectancy (PE), effort expectancy (EE), and behavioral intention (BI).

As shown in Figure 3 and Table 4, both behavioral intention ($\beta = 0.694$, $p < 0.05$) and facilitating conditions ($\beta = 0.179$, $p < 0.05$) significantly predict the actual usage of AI tools. This indicates that students' willingness to adopt AI is the most powerful driver of actual use, confirming UTAUT's assertion that intention acts as the primary mechanism through which perceptions are translated into behavior. The strong coefficient for behavioral intention suggests that when learners perceive clear value in AI tools, they are highly likely to integrate them into their writing practices. Facilitating conditions also play a role, but their smaller coefficient implies that institutional support and infrastructure function as enabling factors rather than direct motivators.

Furthermore, performance expectancy ($\beta = 0.111$, $p < 0.05$), effort expectancy ($\beta = 0.276$, $p < 0.05$), and social influence ($\beta = 0.856$, $p < 0.05$) significantly influence learners' intentions to use AI-based technologies for improving their writing skills. Among these, social influence emerged as the strongest predictor, highlighting the central role of peers, instructors, and academic culture in shaping adoption. This finding resonates with studies in collectivist educational contexts, where learners' decisions are often embedded in social expectations rather than purely individual preferences. Effort expectancy also demonstrated a meaningful effect, suggesting that students are more likely to intend adoption when they perceive AI tools as easy to use and cognitively undemanding. The weaker, yet significant, contribution of performance expectancy indicates that while students recognize the potential benefits of AI for writing quality, this perception alone is insufficient without ease of use and social validation.

Conversely, the link between facilitating conditions and behavioral intention is not statistically significant ($\beta = 0.064$, $p > 0.05$), which suggests that although institutional resources and training support the actual use of AI tools, they do not substantially shape students' initial intentions to adopt. This result diverges from studies conducted in technologically advanced environments, where facilitating conditions often play a stronger role. It may reflect the Omani higher education context, where personal motivation and peer influence outweigh institutional drivers in early stages of adoption.

Table 4. The direct hypotheses

Structural Path		β (>0.2)	C.R (>0.196)	P-value	Decision
H1	IB → UB	0.694	13.414	0.000	Supported
H2	FC → UB	0.179	3.969	0.000	Supported
H3	PE → BI	0.111	2.696	0.007	Supported
H4	EE → BI	0.276	7.127	0.000	Supported
H5	SI → BI	0.586	10.865	0.000	Supported
H6	FC → BI	0.064	1.590	0.112	Not Supported

4-4- The Mediation Effect

The results provide robust evidence supporting the mediating role of behavioural intention in linking the external variables—social influence, performance expectancy, and effort expectancy—to the actual use of AI-based writing tools among EFL learners. This mediation pattern aligns with the theoretical expectations outlined in hypotheses H7, H8, and H9. As presented in Table 4, the bootstrap analysis yielded standardized indirect effect values that clarify how these predictors influence usage behaviour through the intermediary of behavioural intention.

For hypothesis H7, the mediation effect from performance expectancy to usage behaviour via behavioural intention was statistically significant, yielding an indirect effect of 0.077 (SE = 0.033, 95% CI: [0.030, 0.139], p = 0.012). A similar trend was observed in hypothesis H8, where effort expectancy indirectly influenced AI tool usage through behavioural intention, with a standardized effect of 0.192 (SE = 0.038, 95% CI: [0.136, 0.259], p = 0.001), indicating both statistical and practical significance. In hypothesis H9, the pathway from social influence to usage behaviour through behavioural intention demonstrated a notable indirect effect of 0.407 (SE = 0.059, 95% CI: [0.311, 0.508], p = 0.001), further confirming the theoretical model's assumptions.

Collectively, these findings offer clear empirical support for the central role of behavioural intention in shaping students' decisions to engage with AI tools in academic writing. The significance of the indirect pathways affirms the impact of psychological and motivational variables in influencing technology adoption within the educational context.

Table 5. Bootstrap Results: Standardized Indirect Effect

Path/effect→		β	SE	95% Interval of Confidence		p-value	Decision
				Lower	Upper		
H7	PE → BI →UB	0.077*	0.033	0.030	0.139	0.012*	Supported
H8	EE → BI →UB	0.192**	0.038	0.136	0.259	0.001*	Supported
H9	SI →BI →UB	0.407**	0.059	0.311	0.508	0.001*	Supported

(*) Statistically Significant (**) Practically Important.

4-5- Moderation Analysis of AI Usage Frequency

A simultaneous analysis was conducted to examine whether AI usage frequency moderates the relationship between students' behavioural intention (BI) and their behavioural usage (BU) of AI tools among Saudi EFL university students. AI usage frequency was categorized into five groups: Never (N = 47), Rarely (N = 28), Sometimes (N = 51), Usually (N = 49), and Always (N = 80). The initial analysis was performed without constraining the path coefficient (BI → BU), and a baseline chi-square value was established. In the subsequent analysis, the path coefficient (BI → BU) was constrained to be equal across different AI usage frequency groups.

The results indicate that the chi-square value of (29.19) exceeded the chi-square critical value of (7.81) at p<0.01, suggesting a significant moderation effect of AI usage frequency on the relationship between behavioural intention and behavioural usage of AI tools. This finding implies that the extent to which students intend to use AI tools translates differently into actual behavioural usage depending on their level of AI engagement. Specifically, the path coefficients varied across the AI usage frequency groups: 0.30 for the Never group, 0.42 for the Rarely group, .58 for the Sometimes group, 0.65 for the Usual group, and 0.75 for the Always group. These results indicate that students who frequently use AI tools (Usually and Always groups) exhibit a stronger relationship between behavioural intention and behavioural usage compared to those who rarely or never use AI tools.

In conclusion, the analysis reveals that AI usage frequency significantly moderates the causal path between behavioural intention and behavioural usage of AI tools (H11). The findings suggest that as students engage more frequently with AI tools, their intention to use them translates more strongly into actual usage. This result has important implications for technology adoption models, indicating that prior exposure and familiarity with AI play a crucial role in shaping students' technology adoption behaviours. Practically, these findings highlight the importance of promoting consistent AI tool usage to reinforce behavioural intentions and facilitate actual adoption.

Table 6. Structural Invariance Analysis of AI Usage Frequency

Path	Model	Chi-squared	df	Critical Value	Chi-squared Change	Result
BI → BU	Unconstrained	1535.298	644	7.81	29.19	S
BI → BU	Constrained	1562.923	647			

(P< 0.01; S = Significant)

5- Discussion

The results of this investigation substantiate the relevance of the UTAUT framework in elucidating the determinants of AI tool adoption among EFL learners for writing enhancement. Among the model's constructs, behavioural intention was identified as the most influential factor predicting actual use of AI technologies; an outcome that corroborates earlier findings underscoring the importance of perceived utility and adoption willingness in driving learner engagement [10, 16]. This highlights the centrality of motivational dynamics in technology uptake, particularly when learners recognize tangible benefits associated with AI tools [13]. Nonetheless, beyond intention alone, elements such as social influence and perceived usability also contribute significantly to students' readiness to utilize these technologies.

Performance expectancy exhibited a positive association with behavioural intention, mirroring evidence that students often regard AI as instrumental in enhancing both the effectiveness and efficiency of their writing tasks [17, 28, 47] . Despite this, apprehensions regarding dependency remain pertinent, particularly the risk that AI-driven feedback may prompt superficial textual adjustments rather than deeper, cognitively demanding revisions [4, 8]. Additionally, effort expectancy emerged as a critical determinant, indicating a student preference for tools with intuitive, user-friendly interfaces—a finding echoed in the work of [12, 30]. However, there is a potential downside; overly streamlined systems may inadvertently discourage engagement with complex writing strategies, potentially undermining the development of higher-order thinking skills [42].

Social influence significantly impacted behavioural intention, highlighting the role of peer and instructor recommendations in AI adoption [36, 37] While such endorsements encourage experimentation, external pressure may lead to superficial AI tool usage rather than meaningful learning engagement [14]. Facilitating conditions positively influenced actual adoption but did not significantly impact behavioural intention, diverging from studies emphasizing institutional support as a driver of technology adoption [10, 38]. This suggests that while access to AI tools facilitates usage, students may view adoption as a personal rather than institutionally driven decision [15].

Prior AI experience was found to moderate the intention-adoption relationship, confirming that students with greater exposure to AI are more likely to integrate it into their writing practices [2, 16] This supports the argument that familiarity with AI enhances confidence and reduces scepticism, whereas students with limited AI experience may hesitate due to technical uncertainties [17]. These findings underscore the need for structured AI literacy initiatives to bridge the gap between intention and adoption.

Overall, this study validates the UTAUT model's relevance in AI adoption among EFL learners while emphasizing the importance of balancing AI integration with pedagogical integrity. Institutions must ensure that AI tools serve as writing enhancers rather than replacements for critical thinking and creativity.

6- Conclusion

The study's findings have significant pedagogical and technological implications. First, educators should emphasize AI tools as writing enhancers rather than substitutes to mitigate over-reliance. AI-generated feedback should be integrated with instructor-led guidance to promote deeper engagement with writing tasks. In practical terms, this means positioning AI as a first layer of support, while instructors encourage students to critically evaluate and expand upon AI suggestions. Assignments that require learners to reflect on and justify revisions made with AI input can further prevent dependency and foster critical thinking.

Second, universities should implement AI literacy programs to improve students' digital competencies, ensuring that adoption is informed rather than passive. Third, AI developers should design intuitive but cognitively stimulating interfaces, encouraging students to engage with complex writing structures rather than relying solely on automated corrections. Fourth, beyond training, universities should establish clear regulatory and ethical frameworks governing AI-supported writing. Such frameworks should address academic honesty, authorship integrity, plagiarism risks, and the protection of student data. By formalizing ethical guidelines at the institutional level, universities can promote responsible use of AI tools, safeguard originality in student work, and provide clarity for both learners and instructors on the boundaries of acceptable AI integration.

6-1- Limitations and Directions for Future Inquiry

Although this research provides important findings, it is necessary to recognize some limitations. To begin with, its cross-sectional nature constrains the ability to draw causal inferences. Subsequent investigations could adopt longitudinal methodologies to observe the evolution of AI adoption across time. Furthermore, the research is contextually situated within the population of Omani EFL learners, which may limit the extent to which the findings are applicable to diverse cultural and linguistic settings. Broader comparative analyses across multiple regions are recommended to enhance external validity. Additionally, reliance on self-reported data introduces the potential for respondent bias. Incorporating alternative data sources, such as system logs or direct observation, could serve to corroborate participants' stated behaviors.

Another important limitation concerns the demographic composition of the sample, which consisted solely of female undergraduates. This raises potential concerns regarding the influence of gender and cultural dynamics on adoption behaviors. In the Omani context, social norms and peer relationships may shape how women perceive and respond to institutional or technological innovations, potentially amplifying the role of social influence observed in the results. Future research should therefore adopt more gender-balanced samples and examine whether male learners, or mixed-gender cohorts, demonstrate different adoption patterns. Comparative studies could also assess how cultural factors such as collectivism, institutional authority, or gender roles mediate the adoption of AI tools across diverse educational settings. Lastly, ethical dimensions associated with AI integration remain insufficiently explored; future studies should investigate implications for academic honesty, authorship integrity, and creativity to ensure responsible and sustainable use of AI in education.In addition, ethical dimensions—such as plagiarism risks, loss of creativity, authorship attribution, algorithmic bias, and data privacy—were acknowledged in this study but not modeled as formal constructs due to scope. Future research should extend the UTAUT framework by operationalizing these ethical considerations as measurable variables. Integrating them into adoption models would provide a more comprehensive understanding of how ethical concerns directly shape learners' intentions and behaviors, ensuring that AI use in education is not only effective but also responsible and sustainable.

6-2- Recommendations

To facilitate the effective incorporation of AI technologies into EFL writing pedagogy, educational institutions are encouraged to introduce formal instructional initiatives aimed at bolstering learners' digital competencies and fostering confidence in utilizing AI-enhanced writing platforms. Such initiatives ought to acquaint students with the operational scope, constraints, and ethical dimensions of AI tools, thereby promoting their responsible and informed engagement. Moreover, the establishment of well-defined institutional frameworks governing AI use is essential, particularly in addressing ethical imperatives such as academic honesty, user data protection, and the preservation of scholarly integrity. Clear usage protocols should delineate how AI-generated content can support, rather than supplant, students' authentic writing practices.

Moreover, educators should adopt a balanced approach to AI integration, reinforcing that AI tools serve as writing enhancers rather than substitutes for critical thinking and creativity. AI-generated feedback should be incorporated alongside instructor-led guidance to encourage deeper engagement with the writing process. Furthermore, AI developers should refine tool interfaces to make them not only user-friendly but also capable of stimulating cognitive engagement. Ensuring that AI tools encourage iterative writing and critical revisions, rather than automated fixes, will better support students' language acquisition and writing development.

Future research should expand the study of AI adoption across diverse cultural contexts, as this study is limited to Omani EFL learners. Comparative research in different regions would offer broader insights into how digital literacy, institutional support, and cultural attitudes influence AI adoption. Additionally, longitudinal studies should be conducted to examine the long-term effects of AI adoption on students' writing proficiency, creativity, and critical thinking skills. Investigating whether prolonged AI usage enhances or diminishes writing competence will provide essential insights for educators and policymakers. By addressing these areas, AI adoption in EFL writing instruction can be refined to maximize its benefits while mitigating potential drawbacks.

With respect to feasibility, some alignment already exists within Omani universities, as several institutions have begun implementing digital transformation initiatives and introducing AI-related discussions into their curricula. However, the full implementation of AI literacy programs, comprehensive training, and robust ethical frameworks will require systemic policy reforms at both the institutional and national levels. Coordinated action by universities, regulatory bodies, and policymakers will therefore be necessary to create a sustainable ecosystem for responsible AI adoption in higher education.

7- Declarations

7-1- Data Availability Statement

The data presented in this study are available in the article.

7-2- Funding

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

7-3- Institutional Review Board Statement

The study was approved by the Institutional Review Board (or Ethics Committee) of A'Sharqiyah University (ASU/UREBC/25/94).

7-4- Informed Consent Statement

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

7-5- Conflicts of Interest

The author declares that there is no conflict of interests 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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