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Bridging technology and confidence: Linking AI acceptance to writing self-efficacy among English instructors

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Abstract

The present study examined the relationship between artificial intelligence (AI) acceptance and writing self-efficacy among 278 Iranian English university instructors. The quantitative findings indicated a statistically significant positive relationship between AI acceptance and writing self-efficacy ($r = 0.42$, $p < 0.01$). The qualitative phase examined the instructors' perceptions and their practices using four main domains from Khalifa and Albadawy's framework (2024). Based on the findings, the interviewees indicated that AI tools had alleviated their writing difficulties in (1) Content Development and structuring, with more experienced instructors utilizing advanced text structuring while novice instructors focused on grammar; (2) Idea Development, where AI warranted research design with assistance particularly in identifying gaps in the literature; and (3) Editing/Publishing support (all users appreciated being able to check for plagiarism, though the more experienced instructors did take advantage of peer revision options); (4) Literature Review and Synthesis, the data showed that instructors evaluated texts differently albeit dependent on experience level. Additionally, it appeared that emotional responses such as enthusiasm or skepticism were also mediating factors that influenced acceptance. Barriers to AI use and acceptance also emerged regarding institutional support and ethical considerations. The data suggest that self-efficacy is influenced positively through prior experience or use, and the self-efficacy gains were more pronounced for more experienced instructors. This reveals how a cycle of adopting technology establishes confidence. The findings suggest that AI benefits are conditional based on experience level, institutional and contextual barriers, emotional factors, and contextual differences providing rich practical insights for training programs.

Keywords: Academic writing; AI acceptance; English university instructors; writing self-efficacy

Introduction

AI has become a game-changer in academic writing, providing tools that assist with research support, writing improvement, data analysis, plagiarism detection, language improvement, and personal feedback (Zawacki-Richter et al., 2019). These tools have the potential to facilitate writing for English as a Foreign Language (EFL) teachers, who are often faced with the difficulties of producing the same level of academic written work while simultaneously balancing the responsibilities of teaching and research (Hyland, 2016). AI-powered writing assistants, such as Grammarly, ChatGPT, and Turnitin, may assist

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with idea generation, grammar correction, enhancement of clarity, and style revision, possibly enhancing both writing quality and their self-efficacy as writers (Divekar et al., 2022).

A variety of factors influence educators' acceptance of AI tools, such as perceived usefulness, ethical aspects, and emotional aspects including confidence gains or concern about authenticity (Hwang et al., 2023). Recent research by Hazzan-Bishara, et al. (2025) identifies key aspects of acceptance of AI among educators and notably found self-efficacy is a significant factor. Alharbi and Drew (2019) reported that self-efficacy may influence perceptions of ease of use and usefulness in their Technology Acceptance Model. There has been a growing interest in using AI tools for academic writing, yet few researchers have studied the relationship between AI tools and writing self-efficacy. Writing self-efficacy is a relevant psychological variable — it relates to instructors' motivation, persistence, and performance (Bandura, 1997). However, other bodies of research have studied similar relationships within educational technology contexts. Some studies have investigated TPACK (Technological Pedagogical Content Knowledge) and self-efficacy, and have found that teachers with stronger technology integration skills demonstrate higher confidence in their teachers' knowledge (Scherer et al., 2019; Wang et al., 2018). Likewise, research into acceptance of online teaching has shown significant correlations with self-efficacy, where instructors with more confidence in technology will tend to hold more positive attitudes towards virtual teaching (Alqurashi, 2019; Martin et al., 2022). Across the literature regarding technology acceptance, studies utilizing the Technology Acceptance Model consistently demonstrate that self-efficacy is a salient predictor of educators adopting and utilizing digital tools (Šumak et al., 2021; Teo et al., 2019). In the context of EFL settings, limited research has been conducted, especially in training contexts lacking resources (Kohnke et al., 2023). As such, the current study will address this gap through an investigation into the relationship between AI acceptance and writing self-efficacy with the Iranian EFL university instructors, who will provide unique challenges and associated perspectives regarding struggles associated with using technology in low-resourced education settings.

Literature review

Writing self-efficacy

According to the cognitive process theory of writing (Flower & Hayes, 1981), writing is an activity that is structured hierarchically and process-oriented, involving the writer's task environment, their long-term memory, and the writing process itself, which are all interconnected and dynamic. Two decades after introducing this theory, Hayes (2000) suggested an updated model that consists of two elements: the task environment and the individual. The task environment includes the social context (such as feedback from teachers or distractions) and the physical context (like available resources or online writing tools) that can have either a positive or negative effect on the writing process. The individual aspect comprises motivation/affect, working memory, and cognitive processes. The task environment influences the writer's emotional and cognitive traits during writing, which then affects their current writing activities (i.e., physical environment). These two interconnected and interactive elements represent the entirety of the writing process. Based on the cognitive process theory, writing is a generative and communicative activity that involves "cognitive, affective, social, and physical conditions" (Hayes, 2000, p. 5). Therefore, cognitive and emotional factors such as self-efficacy and self-regulation play a crucial role in determining writing outcomes.

A substantial amount of research has explored the connection between writing self-efficacy and writing proficiency (e.g., Prat-Sala & Redford, 2012; Villalón, Mateos, & Cuevas, 2013). Studies have also revealed a mediating effect of writing self-efficacy on the relationship between writing proficiency and emotional constructs (such as anxiety or motivation) (Woodrow, 2011). Students who were self-efficacious in their writing demonstrated higher levels of motivation (Zhang & Guo, 2012) and ultimately performed better in writing tasks (Woodrow, 2011).

Technology Acceptance Models

The Technology Acceptance Model (TAM) was introduced by Davis in 1989 to assess students' acceptance of four different programs. In his original study, Davis established the connections among perceived usefulness, perceived ease of use, attitudes, and the actual usage of the programs. The traditional model was developed to clarify and forecast the acceptance of technology users based on multiple factors, yet it remains receptive to newly emerging constructs, as noted by Cheung and Vogel (2013) since the elements in the original TAM did not provide extensive detail regarding technology usage and acceptance. Venkatesh and Davis later expanded the model into TAM 2 (the Extended Technology Acceptance Model) by incorporating social and cognitive factors, such as experience and voluntariness in 2000, which prompted further investigations into the moderating effects of these elements, as noted by Venkatesh and Bala (2008).

A number of factors may affect teachers' technology acceptance. In fact, previous research indicates that the subject being taught can influence the extent of technology integration, although the results are not always consistent. For instance, Zhao and Frank (2003) conducted a study that showed high school teachers, particularly those teaching English, were more inclined to incorporate technology into their lessons compared to their peers in other subjects. Similarly, Hechter and Vernette (2013) discovered that the concerns about and the conditions favorable to technology integration differ by educational level, with middle and high school educators facing different challenges than those teaching at the elementary level. The experience level of teachers

also plays a critical role in the adoption of technology, according to existing research. Liu et al. (2017) identified a negative correlation between the number of years teachers had taught and their confidence and comfort in using technology. In the meantime, institutional obstacles can have a significant role in adopting AI and restrict the technology's potential to enhance self-efficacy. Selwyn (2022) highlights that structural barriers in educational systems such as insufficient educational programs, restricted access to resources, and institutional policies can greatly impede the integration of technology. Emotional factors are yet another important aspect in the domain of technology acceptance. Hazzan-Bishara et al. (2025) note that the affective factors, from self-efficacy to anxiety, enable educators to interact with emerging technologies. Contextual and cultural factors further mediate the incorporation of technology particularly in a specific educational setting such as the Iranian EFL contexts. Kohnke et al. (2023) state the barriers to the adoption of technology in the form of resource-limited teachers, especially in terms of limited technological infrastructure and cultural skepticism about AI's appropriateness in academic writing. These results align with the extended TAM (Alharbi & Drew, 2019) as it relates perceived usefulness as one of the determinants of adoption to institutional, emotional, and cultural factors. These elements clarify why patterns of technology adoption and their impact on affective factors, particularly self-efficacy, can differ greatly in various educational contexts.

AI Acceptance and Writing Self-Efficacy

The integration of AI tools in academic writing has changed educational practices, yet its relationship with the self-efficacy of teachers seems to be unexplored. Self-efficiency, which is defined as a person's belief in his ability to successfully execute tasks (Bandura, 1997), plays an important role in adopting teachers' technology. Research indicates that high self-efficiency instructors are more likely to embrace innovative devices, as they see them as opportunities rather than threats (Scherer et al., 2021). In the context of AI, acceptance is often measured through frameworks such as the TAM, which highlights the ease of use (Davis, 1989) perceived usefulness, and ease of use as major determinants. Recent studies suggest that AI tools (e.g., ChatGPT, Grammarly) mitigate writing challenges—such as grammar correction and idea generation—thereby boosting confidence, particularly among novice instructors (Konke et al., 2023). However, concerns about skepticism and moral implications (Bednar et al., 2021), persist.

The findings show a differential impact on AI according to teachers' experience (Chen et al., 2025). For instance, those with more experience tend to use AI for higher-order thinking tasks, such as literature analysis and peer review, whereas those with less proficiency are more inclined to focus on teaching lower-order skills, such as grammar (Khalifa & Albadawy, 2024). Institutional support also mediates this relationship: for those who have received less training, the hesitance is greater and is diminished through structured programs that enhance self-efficacy (Hwang et al., 2023).

AI in Academic Writing

The adoption of AI-powered writing tools in EFL classrooms is on the rise. These tools encompass grammar checkers, writing assistants, and programs capable of generating essays independently. They are user-friendly and efficient, providing significant time and effort savings for both learners and instructors (Gayed et al., 2022). Moreover, AI writing tools have shown particular effectiveness for EFL students with limited English proficiency. By utilizing these tools, learners can obtain quick feedback and support, leading to a more rapid enhancement of their writing skills. Generally, AI writing applications are designed to evaluate written content and offer insights into various aspects of writing, including grammar, vocabulary, syntax, content, and organizational structure (Thorp, 2023). This feedback is generated through machine-learning algorithms that assess the text against an extensive database of correct and incorrect writing examples. The implementation of AWE in educational settings has sparked discussion, similar to various other instructional technologies. On one hand, AWE is lauded as a means to free teachers, allowing them to allocate more time to teaching writing rather than focusing solely on grading tasks (e.g., Burstein, et al., 2004, Li, 2025). However, the belief that computers can provide valuable writing critiques has led to considerable skepticism, with some research showing mixed results concerning AWE's effectiveness (Chen & Pan, 2022; Fereidouni & Farahian, 2024). AWE systems frequently have difficulty grasping the nuances and subtleties of written work, resulting in feedback that can be either irrelevant or inappropriate (Baker & Inventado, 2014). Moreover, these systems typically concentrate on surface-level mistakes, prioritizing grammatical accuracy while overlooking higher-order issues such as coherence, argumentative quality, and overall writing proficiency (Chalhoub-Deville, 2018). AWE systems also tend to deliver generic feedback that fails to consider individual writing styles or the unique needs of various learners, which hampers their overall effectiveness (Bae, 2016; Fu et al., 2022). Furthermore, students may become excessively dependent on AWE for feedback, which can impede the development of their self-editing abilities and their capacity to critically assess their writing (Wang, 2019).

The incorporation of AI into academic writing has gained notable significance, providing solutions to various challenges. A systematic literature review conducted by Khalifa and Albadawy (2024) identified six key domains (see Figure 1) in which AI facilitates academic writing and research: 1) facilitating idea generation and research design, 2) improving content and structuring, 3) supporting literature review and synthesis, 4) enhancing data management and

analysis, 5) supporting editing, review, and publishing, and 6) assisting in communication, outreach, and ethical compliance. These domains have been utilized in the current study as a framework for content analysis.

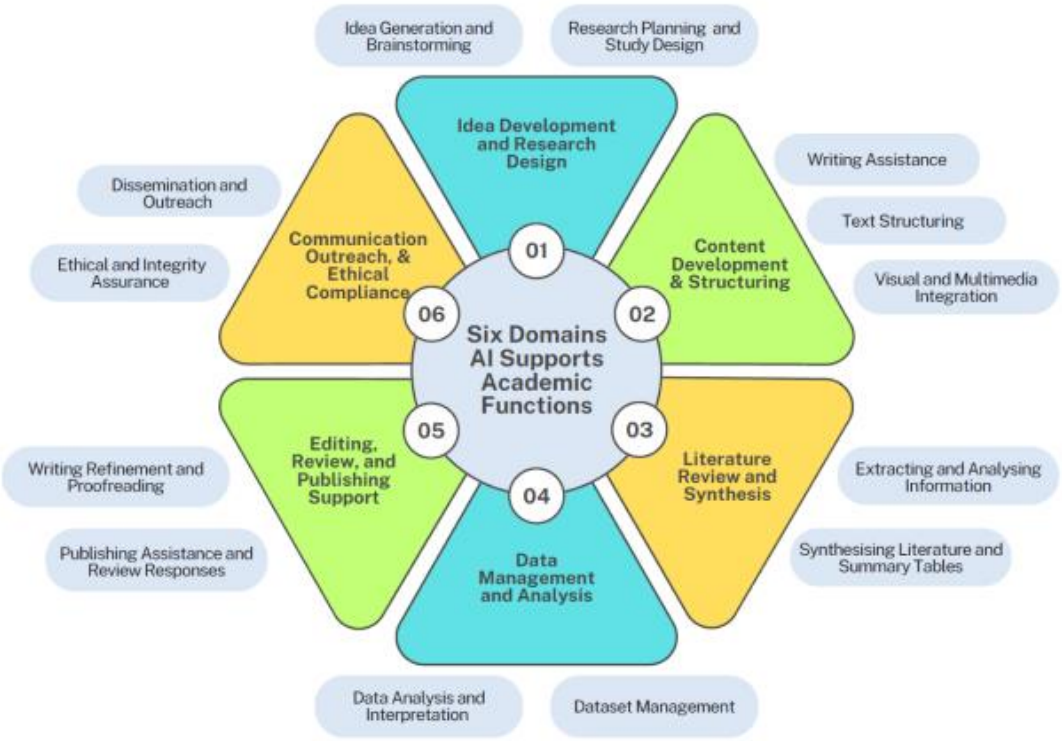

Figure 1.

The six domains where AI can improve academic functions. Adapted from Khalifa, M., & Albadawy, M. (2024). Using artificial intelligence in academic writing and research: An essential productivity tool. *Computer Methods and Programs in Biomedicine Update, 5*, Copyright © 2024 by Elsevier.

Although there is an ever-growing interest in the role that AI plays in education, few if any research has investigated the interplay between AI acceptance and *writing self-efficacy* among English teachers and educators, especially at the university level. Whereas the existing research studies promote the general effect of technology on self-efficacy (Teng & Zhang, 2016; Kohnke et al., 2023) and the hurdles of using AI (Selwyn, 2022), the *instructor-specific* interplay between taking advantage of AI tools and confidence in teaching writing has not been adequately studied. For example, research studies such as Zawacki-Richter et al. (2019) concentrate on the broad educational potential of AI but ignore contextual factors (e.g., institutional support, prior experience) that can intervene in this relationship between teachers and instructors. Meanwhile, ethical concerns (Bender et al., 2021) and emotional responses (Scherer et al., 2021) are often studied in isolation rather than integrated as part of a holistic framework relating AI acceptance to self-efficacy. This study intends to fill these gaps by investigating how perceived usefulness, ease of use, and institutional training shape instructors' writing self-efficacy, filling a critical void in the literature on AI's *professional* (not just pedagogical) implications. To this end, the following research questions were proposed:

RQ1: Is there a significant relationship between English instructors' AI acceptance and their writing self-efficacy in academic writing?

RQ2: How do English instructors perceive the role of AI tools in overcoming challenges in academic writing (e.g., idea generation, grammar, plagiarism), and what emotional or cognitive factors influence their acceptance?

RQ3: What are the barriers to using AI for academic writing, and how do these practices shape English instructors' self-efficacy in their writing abilities?

Methodology

Participants

This study included 278 Iranian EFL university teachers (93 females, 185 males) who were recruited via convenience sampling from public and private institutions. The participants were qualified to teach English language for English Language Teaching (57%), Translation (28%), or Literature (15%). The experienced instructors were regarded as those who had at least

Article in

five or more than five years of teaching English in universities (Nazari, et al., 2019). All instructors were actively engaged in academic writing tasks (e.g., research publication, student feedback, thesis supervision, working on PhD dissertations) while teaching either general English (62%) or discipline-specific courses (38%) across proficiency levels. During the sampling period, participants were actively engaged in academic writing tasks (research articles: 82%, working on PhD dissertations: 41%, thesis supervision: 63%) while teaching general English (62%) or discipline-specific courses (38%). For the qualitative dimension, we conducted semi-structured interviews with 22 instructor-volunteers purposively selected from the larger pool to represent varying AI adoption levels (7 daily users, 9 weekly users, 6 occasional/non-users), and disciplinary backgrounds (13 English language teaching, 5 Translation, 4 Literature) from both public (n=21) and private (n=10) institutions. We implemented member checking with five participants and achieved strong inter-coder reliability (κ=.82) to validate thematic findings, with all data anonymized through pseudonyms (e.g., "Prof. Tehrani") and translated with cultural-linguistic sensitivity. The sample size was determined by thematic saturation, which was reached when no new patterns emerged in the final three interviews.

Instruments

AI acceptance in academic writing

The impetus for creating the scale originated from another research initiative being undertaken by the first researcher of the present study. It draws on the TAM (Davis, 1989). Exploratory factor analysis was conducted to identify the underlying constructs. The initial Kaiser-Meyer-Olkin (KMO) result of 0.69 was deemed inadequate. After removing four items with low factor loadings (below 0.50) and reapplying the factor analysis, the KMO improved to 0.77. Bartlett's Test of Sphericity also demonstrated statistical significance ($\chi 2\ (478) = 5346.11$, $p = 0.000 < 0.05$). A principal component factor analysis with Varimax rotation revealed that all items had acceptable loadings. Ultimately, 27 items remained, forming the final version of the scale. A 5-point Likert scale was used, from strongly agree to strongly disagree. The items included perceived usefulness (8 items), perceived ease of use (4 items), attitudes toward utilizing (4 items), behavioral intentions to employ AI (5 items), and AI digital literacy in academic writing (6 items).

Teacher writing self-efficacy scale.

Based on Teng et al. (2017), we designed the first draft of the Teacher Writing Self-Efficacy Scale (IWSS) across linguistic, self-regulatory, and performance dimensions. As the first step, we prepared the first draft which contained 25 items. Then, we invited four experts in TEFL and teacher education to evaluate the items for clarity, relevance, and theoretical alignment. Based on the feedback we received, two items were removed**,** and the remaining 23 items were revised. A principal component analysis was then run to validate the scale. The correlation matrix showed that eight items had weak loadings and were subsequently eliminated. After rerunning the analysis, the KMO measure (0.78) and Bartlett's Test of Sphericity ($\chi^2\ (210) = 2986.35$**,** $p < 0.001$**)** confirmed the data's suitability for factor analysis. The final 15-item scale demonstrated clear factor loadings using Varimax rotation. Each item was anchored to a 7-point Likert scale with a 7-point Likert scale ranging from 1 (not at all true of me) to 7 (very true of me). The scale's reliability was acceptable, with Cronbach's $\alpha = 0.87$, which indicated high internal consistency.

Semi-structured interviews

Semi-structured interviews were employed to explore the participants' views on research questions 3 and 4 (See Appendix). Interviews were carried out with 22 participants from the second experimental group. Prior to the interviews, the participants were informed about the purpose of the discussion. They were also assured that their responses would remain confidential and that their identities would not be disclosed. Each interview comprised five open-ended questions and lasted approximately 30 to 45 minutes. The interviews took place in English via Skype with the selected participants of the research. Subsequently, all recorded interviews were transcribed for thematic analysis.

Data Collection Procedure

The researchers employed either convenience sampling or voluntary response sampling to distribute questionnaires to English instructors. The surveys were available in both digital and printed forms, depending on the participants' preferences and accessibility. Before beginning the data collection, the researchers ensured that participants were well-informed about the study's goals, the voluntary nature of their involvement, and the confidentiality of their responses. Clear instructions were provided to help ensure that the surveys were completed accurately and comprehensively. In the qualitative phase, the participants were invited to take part in one-on-one interviews that lasted between 30 and 45 minutes. These interviews were conducted via Google Meet, with some occurring in person based on the participants' preferences. The interviews were recorded with all participants' consent and were transcribed verbatim for subsequent analysis. The data collection process spanned over a period of 6 weeks. Throughout this time, all instructors were involved in various academic writing activities (such as publishing research, providing student feedback, theses/ dissertation supervision, and working on PhD dissertations) in conjunction with their teaching responsibilities. We removed the participants who reported not performing any of these activities. This was done through a screening question in the survey.

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Data Analysis

Descriptive statistics, such as means and standard deviations, were computed for all variables, and the internal consistency of the scales was assessed using KR-21 reliability indices, considering scores above 0.70 to be acceptable. Furthermore, Pearson correlation coefficients were utilized to investigate the relationships between the two variables, offering insights into the strength and direction of these relationships. This systematic method guaranteed the credibility and accuracy of the study's quantitative results. In terms of thematic analysis, the researchers employed an open-coding approach to analyze the gathered data inductively through a three-phase process consisting of open-coding, axial coding, and labeling (Merriam & Tisdell, 2015). Initially, all data from the interview transcripts and surveys were meticulously reviewed and examined iteratively by the researchers to identify meaningful segments relevant to the research questions (open coding). Next, the identified segments were categorized based on their thematic similarities through axial coding, and appropriate labels were assigned according to their content (labeling). The themes were developed using a data-driven approach derived from grounded theory methods, which provide "systematic, yet flexible guidelines for collecting and analyzing qualitative data to construct theories 'grounded' in the data themselves" (Charmaz, 2006, p. 2). To ensure consistency in data categorization, all researchers independently categorized the data with an agreement of approximately 90%. Any areas of disagreement were addressed through discussion.

Results

Quantitative Results

Findings for RQ1: Relationship between AI Acceptance and Writing Self-efficacy

The study examined the relationship between AI acceptance and writing self-efficacy among 278 Iranian English university instructors. Initial data screening confirmed the suitability of the data for parametric analysis. As shown in Table 1, standardized z-scores for both variables fell within the acceptable range of ±3.29 ($p < .001$), indicating no univariate outliers were present in the dataset.

Table 1

Standardized Scores for Checking Univariate Outliers

Variable	N	Minimum	Maximum
Zscore: AI Acceptance	278	-2.45	2.37
Zscore: Writing Self-Efficacy	278	-2.30	2.52

Multivariate normality was assessed using Mahalanobis distances (Table 2). The maximum distance of 8.95 was below the critical χ^2 value of 13.81 for df = 2 at $p < .001$, confirming no multivariate outliers influenced the results.

Table 2

Mahalanobis Distances for Checking Multivariate Outliers

N	Minimum	Maximum	Critical χ^2 Value
278	0.03	8.95	13.81

Normality assumptions were further supported by skewness and kurtosis indices (Table 3). All values fell within recommended ranges (±2 for skewness, ±7 for kurtosis), with AI acceptance (skewness = -0.12, kurtosis = -0.45) and writing self-efficacy (skewness = 0.08, kurtosis = -0.62) showing approximately normal distributions.

Table 3

Skewness and Kurtosis Indices for Normality Assessment

Variable	Skewness	Std. Error	Kurtosis	Std. Error
AI Acceptance	-0.12	0.15	-0.45	0.29
Writing Self-Efficacy	0.08	0.15	-0.62	0.29

Descriptive statistics revealed moderate to high levels of both constructs (Table 4). AI acceptance (M = 85.34, SD = 12.67) showed slightly higher average scores than writing self-efficacy (M = 72.18, SD = 10.45). Both scales demonstrated good internal consistency, with KR-21 reliability coefficients of 0.82 and 0.79 respectively, exceeding the 0.70 threshold for acceptability (Fulcher & Davidson, 2007).

Table 4

Descriptive Statistics and Reliability Indices

Variable	Mean	SD	Variance	KR-21 Reliability
AI Acceptance	85.34	12.67	160.53	0.82
Writing Self-Efficacy	72.18	1045	109.20	0.79

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Pearson correlation analysis (Table 5) revealed a statistically significant, moderate positive relationship between AI acceptance and writing self-efficacy ($r(276) = .42$, $p < .01$). This effect size suggests that approximately 17.6% of the variance in writing self-efficacy can be explained by AI acceptance ($r^2 = .176$), indicating a meaningful though not exhaustive relationship between these constructs in the Iranian EFL context.

Table 5

Pearson Correlations between AI Acceptance and Writing Self-Efficacy

Variable	1	2
1. AI Acceptance	1	.42**
2. Writing Self-Efficacy	.42**	1

**p < .01 (2-tailed)

The results collectively suggest that Iranian English instructors who report greater acceptance of AI technologies tend to demonstrate higher levels of confidence in their writing capabilities, with this relationship being statistically significant but moderate in strength. These findings align with emerging literature on technology integration in EFL contexts while highlighting the unique cultural and professional dynamics of Iranian higher education settings.

Qualitative results:

Findings for RQ2: Perceptions of AI Tools and Influencing Factors

The second research question inquired how English instructors perceive the role of AI tools in overcoming challenges in academic writing (e.g., idea generation, grammar, plagiarism), and what emotional or cognitive factors influence their acceptance.

The qualitative findings revealed distinct patterns in how English instructors perceived AI tools for overcoming academic writing challenges, with notable differences between experienced and novice users. The study focused on four significant areas from Khalifa and Albadawy's (2024) study. We demonstrated the interviewees' perceptions through quotes.

Content Development and Structuring

Grammar and Clarity Improvement:

The participants considered AI tools as effective at advancing language and readability in academic writing. In particular, a novice instructor noted,

> *"I can't live without Grammarly. I can use it to catch those tiny grammar mistakes that I would naturally overlook."*

An experienced user-added,

> *"ChatGPT helps me paraphrase entire paragraphs without losing the academic complexity of my arguments. I can give the manuscript a consistent voice over several pages."*

Tonal Adjustments:

The interviewees described contrasting experiences regarding AI use in their academic writing. A somewhat novice and skeptical instructor explained,

> *"When I use the AI to generate formal tone suggestions it produces an output that is often highly unnatural. This distorts my own scholarly voice."*

On the positive side, another interviewee said:

> *"I often carefully edit the AI's stylistic recommendations to achieve a polished and authentic academic tone that meets publication standards."*

Idea Development and Research

Brainstorming Applications:

AI was categorically utilized based on researchers' experiences in generating and refining ideas. An experienced instructor explained,

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"Before writing my paper I ask the AI to generate an outline for my work."

A novice user on the other hand expressed:

"I usually receive so many random disconnected ideas from AI that instead of actually developing any ideas I end up spending more time trying to organize them."

Literature gap identification:

While the respondents utilized AI as a starting point to signal research gaps, they asserted that the output that AI provides should always be validated. As a cautious instructor shared,

"While the AI may quickly pull up potential gaps, I always validate those suggestions against up-to-date publications because I have seen cases where AI missed important studies."

Editing and publishing support

Plagiarism detection:

Most respondents had oppositional views about leveraging AI for plagiarism detection. As one instructor explained,

"*AI plagiarism checks give me confidence my work* is being held to *academic* rigor."

Whereas another expressed,

"Overly relying on plagiarism checks might make us less critical thinkers about what we consider original or not."

Peer Review Preparation:

Researchers highlighted different methods of using AI to assist with peer review feedback. According to a senior researcher,

"I use AI to draft initial responses to reviewer comments, which I then revise extensively."

An early career instructor opined,

"I fear that journal editors may view my use of AI as posing a threat to the authenticity of my revisions."

Emotional Influences

Anxiety and skepticism:

Anxiety and skepticism were more evident in the novice interviewees' responses**.** One shared that,

"My primary concern is that depending on these tools may wear down my self-editing capacity."

In sum, the key distinction between novice and experienced instructors is that AI is typically described by several experienced instructors as an intelligent collaborator who augments the scholarly judgment rather than replacing it. In contrast, it has often been termed by inexperienced users as either

"Honestly, these tools are great when you're starting out, but they low-key mess with your whole idea of what 'original' really means."

"These tools help beginners but also make us question what originality really means."

Table 6

EFL Instructors' Perceptions of AI Tools in Academic Writing

Domain	Theme	Participant Perspectives	Representative Quotes
Content Development & Structuring	*Grammar & Clarity Enhancement*	Novices valued basic error correction; Experts used AI for advanced refinements.	*"I can't live without Grammarly. I can use it to catch those tiny grammar mistakes that I would naturally overlook".* *"ChatGPT helps me paraphrase entire paragraphs without losing the academic complexity of my arguments. I can give the manuscript a consistent voice over several pages.'"*

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Domain	Theme	Participant Perspectives	Representative Quotes
Idea Generation & Research Design	*Tonal Adjustments*	Skeptics distrusted AI's authenticity; Enthusiasts adapted outputs	*"When I use the AI to generate formal tone suggestions it produces an output that is often highly unnatural. This distorts my own scholarly voice.'"* *" I often carefully edit the AI's stylistic recommendations to achieve a polished and authentic academic tone that meets publication standards '"*
	Brainstorming	Experts used AI strategically; Novices felt overwhelmed	*"Before writing my paper I ask the AI to generate an outline for my work."* *"A novice user expressed, 'The AI generates too many disjointed ideas.'"*
	Literature Gap Identification	All users verified AI suggestions, citing accuracy concerns	*A cautious instructor noted, "'I cross-check AI-identified gaps against recent studies.'"*
Editing & Publishing Support	*Plagiarism Detection*	Valued for integrity checks but raised dependency concerns	*One instructor emphasized, "AI plagiarism checks give me confidence my work is being held to academic rigor."* *"Another cautioned, Overly relying on plagiarism checks might make us less critical thinkers."*
	Peer Review Preparation	Experts refined AI drafts; Novices feared inauthenticity	*"I use AI to draft initial responses to reviewer comments, which I then revise extensively."* *"I fear that journal editors may view my use of AI as posing a threat to the authenticity of my revisions*."
Emotional Influences	*Anxiety & Skepticism*	Stemmed from skill atrophy concerns	*My primary concern is that depending on these tools may wear down my self-editing capacity "*

Results for RQ3: Practices, Barriers, and Their Impact on Writing Self-Efficacy

The third research question explored the practices and barriers to using AI for academic writing, as well as how these practices shape English instructors' self-efficacy in their writing abilities. The qualitative findings revealed distinct patterns in AI adoption, institutional challenges, and the resulting effects on self-efficacy, with notable differences between experienced and novice instructors.

1. Practices in AI Utilization

Editing and Publishing Support

Plagiarism Detection:

Every participant was appreciative of AI tools for checking plagiarism, yet, the more experienced instructors were better able to navigate plagiarism detection in the larger context of considering overall manuscripts during the review. One instructor articulated,

"AI helps me with writing, so I do not look at it through a manual check too to check for originality."

A hesitant novice participant declared,

"I fear editors will dismiss AI-assisted revisions".

Literature Synthesis

Critical Evaluation:

Experienced instructors relied more directly on AI outputs, without struggling at times to be as critical of them.

One experienced interviewee remarked.

"I have tried the tool many times. I know how to use it so I can rely on the output generated."

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Such words illustrate a more cautious perspective of the novice group contrary to those who were still considered experienced. They used AI to identify literature gaps but rigorously cross-referenced the suggestions. As one interviewee noted,

> *"Sometimes I think I should stop using this tool. I cross-check them (the output) with recent studies but again the result is not reliable."*

Five other novice instructors were not so disappointed since they did not know how AI tools work. One stated,

> *"I don't know how it works. My colleagues say you ask it to do something, for example, to write the introduction of your paper, and it generates it for you".*

Content Development

Advanced Structuring:

Experienced instructors employed AI for high-level revisions (e.g., argument coherence). One participant stated that,

> *"AI helps me reorganize sections while maintaining logical flow."*

Novices were most interested in grammar and improvement of clarity.

> *"I employ AI mainly for low-level fix-ups—fixing grammatical mistakes or splitting up awkward sentences."*

2. Barriers to AI Integration

Institutional Support Limitations

Fifteen participants pointed to the limited availability of resources from the institution, including training support and limited access to paid resources. A mid-career instructor noted,

> *"Our university provides no guidance on using AI ethically. It's just us trying to fumble through on our own".*

Ethical Concerns

Although the experienced instructors seemed to know how to use AI tools they did not totally rely on it to produce the first or the main draft. Eighteen of this group of participants articulated ethical issues. This included over-reliance on AI and authorship ambiguity. An instructor admitted,

> *"I avoid AI for drafting. This is because it blurs the line between my work and the work the AI produces."*

Most of the novice instructors had no idea what problems AI-generated texts may produce. Only one was skeptical and expressed her view as,

> *"I do not think AI tools can replace human beings. How can one rely on the things they produce?"*

Experience-Level Disparities

While novices reported feeling overwhelmed by AI's complexity, experienced users emphasized the need for tailored training. One novice instructor shared,

> *"I'd use AI more if there were workshops on how to use it."*

Six experienced instructors like the novices requested help but said that they knew AI basics but they needed help and more training on its different functions. One stated:

> *"I know that skillful prompting helps a lot. I wish there were some workshops to teach me the details."*

Self-Efficacy Impacts

While quantitative data revealed that self-efficacy gains were higher among experienced instructors compared to novices, qualitative findings contextualized this disparity:

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Several instructors reported positive psychological effects resulting from their employment of AI within academic writing. One instructor remarked,

> *"I feel more confident now than ever in my writing using AI-based tools because I know I have a sophisticated second set of eyes catching those issues I might miss."*

Experienced Instructors:

Framed AI as a *"collaborator"* that enhanced their capabilities, leading to greater confidence in writing quality and efficiency.

Novice Instructors: Viewed AI as either a *"crutch"* or a *"disruptive force"*, with self-efficacy gains tempered by uncertainty about long-term skill development.

While, as reported by the interviewees AI tools supported writing tasks, their impact on self-efficacy was mediated by some factors such as the interviewees' experience level, and emotional factors. Experienced instructors applied AI more effectively and this increased their confidence; however, novices encountered more difficulty mastering the technology and voiced more hesitations. In this regard, an experienced instructor said,

> *"AI enhances my capabilities without replacing my judgment."*

A novice instructor expressed her view as,

> *"I worry about losing my editing skills".*

Table 7.

Practices, Barriers, and Self-Efficacy Impacts of AI Adoption in Academic Writing

Category	Theme	User Group	Key Findings	Representative Quotes
Practices	*Editing & Publishing*	Experienced instructors	Strategic use of AI for plagiarism checks and peer review preparation	*"AI helps me with writing, so I do not look at it through a manual check to check for originality."*
		Novice instructors	Hesitancy in using AI for peer review due to authenticity concerns	*"I fear editors will dismiss AI-assisted revisions".*
	Literature Synthesis	Experienced instructors	Heavy reliance on AI outputs with limited critical assessment	*"I have tried the tool many times. I know how to use it so I can rely on the output generated."*
		Novice instructors	Not aware of or critical of AI	*"Sometimes I think I should stop using this tool."*
	Content Development	Experienced instructors	Advanced use for argument coherence and structuring	*"AI helps me reorganize sections while maintaining logical flow."*
		Novice instructors	Focus on basic grammar and clarity improvements.	*"I employ AI mainly for low-level fix-ups—fixing grammatical mistakes or splitting up awkward sentences."*
Barriers	*Institutional Support*	All users	Lack of training and restricted access to premium tools	*"Our university provides no guidance on using AI ethically. It's just us trying to fumble through on our own".*
	Ethical Concerns	Experienced users	Worries about over-reliance and authorship ambiguity	*"I avoid AI for drafting. This is because it blurs the line between my work and the work the AI produces."*
		Novice instructors	Not aware of the problems	
	Experience Gaps	Novice instructors	Feeling overwhelmed by AI's complexity	*"I'd use AI more if there were workshops on how to use it."*
Self-Efficacy Impacts	*Confidence Gains*	Experienced instructors	View AI as a collaborator	*"AI enhances my capabilities without replacing my judgment."*
		Novice instructors	View AI as a crutch/disruptive force	*"I worry about losing my editing skills."*

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Discussion

The first research question investigated the interaction between AI acceptance and writing self-efficacy of EFL instructors. The quantitative results revealed a statistically significant positive correlation, demonstrating that instructors who accepted the AI tools more readily, reported that their self-efficacy in academic writing was higher. This finding is not surprising and aligns with Bandura's (1997) self-efficacy theory, which assumes that support or assistance leads to improved perceived competence. However, the moderate strength of the correlation may suggest that AI acceptance is to a substantial extent influenced by other factors. We assume that experience-level disparities, institutional and contextual barriers, emotional factors, cultural differences were the reasons for the low relationship. Among these factors, we believe that the differences between the instructors' experience levels were of crucial importance, as the findings revealed that novice instructors often struggled to use AI tools, primarily for basic corrections (e.g., grammar checks) rather than higher-order tasks (e.g., argument structuring). This limited utility may have negatively affected self-efficacy gains compared to experienced instructors, who reported higher confidence due to their strategic use of AI (e.g., literature synthesis, peer review preparation). Institutional barriers may also have influenced the correlation in the present study and inadequate support may have restricted AI's potential to promote self-efficacy. This is echoed in one instructor's explanation when he noted, “Our university provides no guidance on using AI”. This highlights how inadequate support restricts AI’s potential to promote self-efficacy.

The finding is partially in line with the literature that demonstrated that TPACK knowledge is one of the predictors of self-efficacy beliefs (Birisci & Kul, 2019; Cankaya, 2018; Kan & Yel, 2019). In addition, in tandem with our finding, as Tokmak and Incikabi, (2013) argue, TPACK-based courses in natural sciences (science education and math) and literature were effective in promoting teachers' self-efficacies. Findings from the study conducted by Abbitt (2011) who explored the interplay between TPACK and the self-efficacy beliefs of pre-service teachers about technology integration revealed the relationship between knowledge and self-efficacy beliefs and underscores the potential areas of knowledge in TPACK domains that influence pre-service teachers' beliefs about technology integration. Such findings are of no surprise since Bandura's (1997) self-efficacy theory clearly argues that mastery experiences—such as successfully utilizing supportive tools—strengthen perceived competence. Likewise, TPACK research similarly supports this process- teachers learn and gain confidence, in part, because of their technological pedagogical knowledge (Abbitt, 2011; Tokmak & Incikabi, 2013). This means that when AI tools provide potential writing support, EFL instructors will experience growth in self-efficacy.

The second research question investigated the university instructors' perceptions of AI tools in overcoming writing challenges. While the experienced instructors strategically used AI for advanced tasks like argument structuring and literature gap identification, novices primarily relied on basic grammar and improvement of clarity. This skill-based disparity reflects Khalifa and Albadawy's (2024) framework of tiered AI adoption in academia. The emotional factors significantly mediated acceptance, with some novice instructors reporting enthusiasm and some others expressing skepticism. These affective responses support Hazzan-Bishara and Levy's (2025) study which explored the role of emotional influences on technology integration. Moreover, the novice struggles with AI-generated ideas ('disconnected concepts') echo Hwang et al. (2023) and Chen et al.’s (2025) findings about novice instructors’ experiences with educational AI. Such skepticism has been reported among Iranian EFL teachers (Neysani, et al., 2023) and it has been reported that teachers working in private institutes hold more positive perceptions toward using technological advancements than public school teachers (Raygan & Moradkhani, 2024).

The instructors' skepticism regarding AI adaptation draws attention to the issue of credibility of AI tools among teachers that is the extent to which one perceives the information in the message to be believable, and unbiased (Moran & Muzellec, 2017). When the source is not regarded as credible, it may have a negative impact on the teacher's willingness to use the AI. The fact that in the present study, the experienced teachers were less skeptical about using AI may reflect the fact that they have learned after extensive use of these tools that they are not supposed to rely on them completely, or perhaps they often check the accuracy of the information provided by AI. This contradicts the results reported by Liu et al. (2017) who found a negative correlation between the length of time teachers had been teaching and their confidence and ease in using technology.

The third research question investigated barriers to AI adoption and their self-efficacy impacts. Although the interviewees reported, that AI tools supported writing tasks, their effect on self-efficacy was mediated by experience level, institutional support, and ethical comfort. While experienced instructors applied AI more effectively and this increased their confidence; novices encountered more difficulty mastering the technology and voiced more ethical hesitations. In addition, institutional limitations and ethical concerns disproportionately affected novices, who viewed AI as either a "crutch" or "disruptive force". This seems consistent with the claim suggested by Rahida Aini et al (2018) who argue that teaching experience impacts teacher performance and teaching effectiveness. This echoes Hazzan-Bishara and Levy (2025) who explain that when teachers view AI tools as advantageous and user-friendly, they are more inclined to incorporate them into their instructional methods, thereby affirming the predictive strength of the TAM in educational settings. This aligns with Selwyn's (2022) documentation of structural barriers in educational technology adoption. The quantitative self-efficacy gains empirically validate Alharbi and Drew's (2019) TAM extension, demonstrating that experience level mediates technology's confidence-building effects. Novice

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requests for prompt engineering workshops suggest targeted training could bridge this gap, as recommended by Kohnke et al. (2023) for EFL contexts. Perhaps, future research is needed to investigate the impact of such factors as teachers' teaching experience, grade, and teaching subject—on their readiness for and attitudes toward AI education.

Conclusion

The present study explored the relationship between AI acceptance and writing self-efficacy among Iranian English instructors. The results revealed a significant but moderate positive correlation. While this aligns with Bandura's (1997) claim that technological supports can improve perceived competence, our mixed-methods findings extend this theory by demonstrating that the relationship is mediated by several factors:

1. Experience-Level: Experienced instructors employed AI for higher-order tasks, resulting in greater self-efficacy gains, whereas novices primarily used AI for basic corrections (e.g., grammar), limiting confidence-building effects.

2. Institutional and contextual barriers: Inadequate training and ethical concerns hindered novices, echoing Selwyn's (2022) observations about structural impediments to technology adoption.

3. Emotional factors: Anxiety, skepticism, and confidence were evident in the interviewees' responses**.** While novice interviewees exhibited more anxiety and skepticism, experienced candidates displayed greater confidence in their answers.

4. Contextual differences: The Iranian EFL context—marked by resource constraints further moderated the strength of the relationship.

These findings show that AI's potential to promote self-efficacy is not automatic but contingent on targeted support.

In light of the findings of the study, educational institutions should address the various factors that could influence AI acceptability from English language instructors. Specifically, effective training programs should be developed to facilitate novice instructors' ability to effectively utilize AI tools, moving their engagement beyond basic levels into higher-order pedagogical functions. In addition, through support systems, institutional and emotional barriers may be addressed to provide a more supportive environment for AI integration within the classroom. By understanding the contextual barriers in the Iranian EFL context, policymakers and education leaders can develop student-centered interventions that support both the use of AI and writing self-efficacy for instructors. In this way, the implications are broader than requiring instructors to simply understand the implications of AI; they require action to provide appropriate engagement with technology from an instructional perspective.

This study has several limitations. Firstly, all variables were assessed through self-report scales and the participants might overestimate their self-efficacy gains, so future research should consider using various assessment methods to enhance objectivity. Secondly, the cross-sectional design precludes causal inferences about how AI adoption longitudinally impacts writing competence. Third, in the present study, we did not account for potential disciplinary differences in AI utilization patterns among ELT, Translation, and Literature instructors. Future studies should consider the differences between disciplinary backgrounds. Finally, although the qualitative sample achieved thematic saturation, the relatively small number of interviewees warrants caution in extrapolating the findings.

References

Abbitt, J. T. (2011). An Investigation of the relationship between self-efficacy beliefs about technology integration and technological pedagogical content knowledge (TPACK) among preservice teachers. *Journal of Digital Learning in Teacher Education, 27*(4), 134-143.

Alharbi, S., & Drew, S. (2019). The role of self-efficacy in technology acceptance. In K. Arai, R. Bhatia, & S. Kapoor (Eds.), *Proceedings of the Future Technologies Conference (FTC) 2018* (Vol. 880, pp. 549–556). Springer. https://doi.org/10.1007/978-3-030-02686-8_85

Alqurashi, E. (2019). Predicting student satisfaction and perceived learning within online learning environments. *Distance Education, 40*(1), 133–148. https://doi.org/10.1080/01587919.2018.1553562

Bae, S. H. (2016). A review of automated writing evaluation systems. *Computers and Composition, 40*, 1–18.

Baker, R. S., & Inventado, P. S. (2014). Educational data mining and learning analytics. In *Learning, design, and technology* (pp. 1–23). Springer.

Article in Press

Bandura, A. (1997). *Self-efficacy: The exercise of control*. W.H. Freeman. https://psycnet.apa.org/record/1997-08589-000

Bender, E. M., Gebru, T., McMillan-Major, A., & Mitchell, S. (2021). On the dangers of stochastic parrots: Can language models be too big? *FAccT*, 610–623. https://doi.org/10.1145/3442188.3445922

Birisci, S., & Kul, U. (2019). Predictors of technology integration self-efficacy beliefs of preservice teachers. *Contemporary Educational Technology, 10*(1), 75-93. https://doi.org/10.30935/cet.512537

Burstein, J., Chodorow, M., & Leacock, C. (2004). Automated essay evaluation: The criterion online writing service. *AI Magazine, 25*(3), 27–36.

Cankaya, P. (2018). The exploration of the self-efficacy beliefs of English language teachers and student teachers. *Journal of Language & Linguistics Studies, 14*(3), 12-23. http://www.jlls.org/index.php/jlls/article/view/724/388

Chalhoub-Deville, M. (2018). Automated writing evaluation: Implications for writing assessment. *Assessing Writing, 38*, 9–19.

Charmaz, K. (2006). *Constructing grounded theory: A practical guide through qualitative analysis*. London: Sage.

Chen, H., & Pan, J. (2022). Computer or human: A comparative study of automated evaluation scoring and instructors' feedback on Chinese college students' English writing. *Asian Journal of Second and Foreign Language Education, 7*, 1–20.

Chen, R., Lee, V.R. & G Lee, M. A. (2025). A cross-sectional look at teacher reactions, worries, and professional development needs related to generative AI in an urban school district. *Educ Inf Technol* . https://doi.org/10.1007/s10639-025-13350-w

Cheung, R., & Vogel, D. (2013). Predicting user acceptance of collaborative technologies: An extension of the technology acceptance model for e-learning. *Computers & Education, 63*, 160–175.

Cotton, D. R. E., Cotton, P. A., & Shipway, J. R. (2023). Chatting and cheating: Ensuring academic integrity in the era of ChatGPT. *Innovations in Education and Teaching International*. https://doi.org/10.1080/14703297.2023.2190148

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly, 13*(3), 319–340. https://doi.org/10.2307/249008

Divekar, R. R., Drozdal, J., Chabot, S., Zhou, Y., Su, H., Chen, Y., & Braasch, J. (2022). Foreign language acquisition via artificial intelligence and extended reality: Design and evaluation. *Computer Assisted Language Learning, 35*(9), 2002–2035. https://doi.org/10.1080/09588221.2021.1879162

Fereidouni, P. Farahian, M. (2024). Is ChatGPT a cure-all? Demystifying the impact of using ChatGPT on EFL learners' writing skill. *Applied Linguistics Inquiry, 2*(1),89-103.

Flower, L., & Hayes, J. R. (1981). A cognitive process theory of writing. *College Composition and Communication, 32*, 365–387.

Fu, Q. K., Zou, D., Xie, H., & Cheng, G. (2022). A review of AWE feedback: types, learning outcomes, and implications. *Computer Assisted Language Learning, 37*(1–2), 179–221.

Fulcher,G.,& Davidson,F. (2007). *Language testing and assessment: An advanced resource book*. Routledge.

Gayed, J. M., Carlon, M. K. J., Oriola, A. M., & Cross, J. S. (2022). Exploring an AI-based writing assistant's impact on English language learners. *Computers and Education: Artificial Intelligence*.

Hayes, J. R. (2000). A new framework for understanding cognition and affect in writing. In R. Indrisano & J. R. Squire (Eds.), *Perspectives on writing: Research, theory, and practice* (pp. 6–44). International Reading Association.

Hazzan-Bishara, A., Kol, O., & Levy, S. (2025). The factors affecting teachers' adoption of AI technologies: A unified model of external and internal determinants. *Education and Information Technologies*. https://doi.org/10.1007/s10639-025-13393-z

Article in Press

Hechter, R. P., & Vermette, L. A. (2013). Technology integration in K-12 science classrooms: An analysis of barriers and implications. *Themes in Science and Technology Education, 6*, 73–90.

Hwang, G. J., Xie, H., Wah, B. W., & Gašević, D. (2023). Vision, challenges, roles and research issues of artificial intelligence in education. *Computers and Education: Artificial Intelligence, 1*, https://doi.org/10.1016/j.caeai.2020.100001

Kan, A. U., & Yel, E. (2019). The relationship between self-efficacy beliefs of teacher candidates and their attitudes about computer-assisted instruction. *International Online Journal of Educational Sciences, 11*(3), 248-264.

Khalifa, M., & Albadawy, M. (2024). Using artificial intelligence in academic writing and research: An essential productivity tool. *Computer Methods and Programs in Biomedicine Update, 5*. https://doi.org/10.1016/j.cmpbup.2024.100145

Kohnke, L., Moorhouse, B. L., & Zou, D. (2023). ChatGPT for language teaching and learning. *RELC Journal, 54*(2), 537–551. https://doi.org/10.1177/00336882231162868

Liu, F., Ritzhaupt, A. D., Dawson, K., & Barron, A. E. (2017). Explaining technology integration in K-12 classrooms: A multilevel path analysis model. *Educational Technology Research and Development, 65*(4), 795–813.

Li, H. (2025). Marvel and machine: The influence of awe on the acceptance of artificial intelligence. *Basic and Applied Social Psychology*, 1–12. https://doi.org/10.1080/01973533.2025.2474436

Li, S., & Huo, S. (2020). Automated writing evaluation systems: An overview and implications for teaching. *Language Learning and Technology, 24*(2), 41–59.

Martin, F., Sun, T., & Westine, C. D. (2022). A systematic review of research on online teaching and learning from 2009 to 2018. *Computers & Education, 159*, 104009. https://doi.org/10.1016/j.compedu.2020.104009

Merriam, S. B., & Tisdell, E. J. (2015). *Qualitative research: A guide to design and implementation*. John Wiley & Sons.

Moran, G., & Muzellec, L. (2017). eWOM credibility on social networking sites: A framework. *Journal of Marketing Communications, 23*(2), 149–161.

Nazari, N., Nafissi, Z., Estaji, M., & Marandi, S. S. (2019). Evaluating novice and experienced EFL teachers' perceived TPACK for their professional development. *Cogent Education, 6*(1).

Neysani, M., Nikbakht, A & Jafari, A. (2023). Exploring Iranian EFL Teachers' Trust in AI-based Education Technology. *Journal of New Advances in English Language Teaching and Applied Linguistics,5*(2),1183-1194.

Prat-Sala, M., & Redford, P. (2012). Writing essays: Does self-efficacy matter? The relationship between self-efficacy in reading and in writing and undergraduate students' performance in essay writing. *Educational Psychology, 32*(1), 9–20.

Rahida Aini, M. I., Rozita, A., & Zakaria, A. (2018). Can teachers' age and experience influence teacher effectiveness in hots? *International Journal of Advanced Studies in Social Science & Innovation, 2*(1), 144–158.

Raygan, A., & Moradkhani, S. (2024). Iranian EFL teachers' perceptions toward technology integration, TPACK, attitudes toward technology, and school climate: The case of public schools versus private institutes. *Technology Assisted Language Education,2*(4),22-44.

Scherer, R., Tondeur, J., & Siddiq, F. (2019). The importance of attitudes toward technology for pre-service teachers' technological, pedagogical, and content knowledge. *Computers & Education, 128*, 311–327. https://doi.org/10.1016/j.compedu.2018.09.010

Scherer, R., Siddiq, F., & Tondeur, J. (2019). The technology acceptance model (TAM): A meta-analytic structural equation modeling approach to explaining teachers' adoption of digital technology in education. *Computers & Education, 128*, 13–35.

Selwyn, N. (2022). *Education and technology: Key issues and debates* (3rd ed.). Bloomsbury Academic.

Šumak, B., Pušnik, M., Heričko, M., & Šorgo, A. (2021). Factors affecting acceptance and use of Moodle. *Educational Technology & Society, 24*(2), 105–119. https://www.jstor.org/stable/27004936

Article in Press

Teng, L. S., Sun, P. P., & Xu, L. (2017). Conceptualizing writing self-efficacy in English as a foreign language contexts: Scale validation through structural equation modeling. *TESOL Quarterly*. https://doi.org/10.1002/tesq.432

Teo, T., Huang, F., & Hoi, C. K. W. (2019). Explicating the influences that explain the intention to use technology among English teachers in China. *Interactive Learning Environments, 27*(4), 460–475.

Thorp, H. H. (2023). ChatGPT is fun, but not an author. *Science: Advanced Materials and Devices, 379*(6630), 313–313.

Tokmak, H. S., & Incikabi, L. (2013). An Investigation of Change in Mathematics, Science, and Literacy Education Pre-service Teachers' TPACK. *Asia-Pacific Educational Research, 22*, 407-415.

Venkatesh, V., & Bala, H. (2008). Technology acceptance model 3 and a research agenda on interventions. *Decision Sciences, 39*(2), 273–315. https://doi.org/10.1111/j.1540-5915.2008.00192.x

Venkatesh, V., & Davis, F. D. (2000). A theoretical extension of the technology acceptance model: Four longitudinal field studies. *Management Science, 46*(2), 186–204.

Villalon, R., Mateos, M., & Cuevas, I. (2013). High school boys' and girls' writing conceptions and writing self-efficacy beliefs: What is their role in writing performance? *Educational Psychology, 35*, 653–674. https://doi.org/10.1080/01443410.2013.836157

Wang, W., Schmidt-Crawford, D., & Jin, Y. (2018). Pre-service teachers' TPACK development. *Computers & Education, 121*, 162–175. https://doi.org/10.1016/j.compedu.2018.03.005

Wang, T. (2019). The role of technology in the writing process: A review of literature. *International Journal of Emerging Technologies in Learning (iJET), 14*(1), 4–14.

Woodrow, L. (2011). College English writing affect: Self-efficacy and anxiety. *System, 39*, 510–522.

Zawacki-Richter, O., Marín, V. I., Bond, M., & Gouverneur, F. (2019). Systematic review of research on artificial intelligence applications in higher education. *International Journal of Educational Technology in Higher Education, 16*(1), 1–27. https://doi.org/10.1186/s41239-019-0171-0

Zhang, Y., & Guo, H. (2012). A study of English writing and domain-specific motivation and self-efficacy of Chinese EFL learners. *Pan-Pacific Association of Applied Linguistics, 16*(2), 101–121.

Zhao, Y., & Frank, K. A. (2003). An ecological analysis of factors affecting technology use in schools. *American Educational Research Journal, 40*(4), 807–840.

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Appendix

Interview Guide

RQ2: Perceptions of AI Tools and Influencing Factors

1. In what ways do you use AI tools (Grammarly/ChatGPT) to address specific issues in a writing context (idea generation, grammar correction, or plagiarism detection)? Please provide a recent example.

2. What feelings do you associate with your use of AI for writing (confidence, anxiety, skepticism)? In what ways do these feelings affect your willingness to rely on AI tools?

RQ3: Barriers and Self-Efficacy Impacts

3. What contextual factors (training, access to tools, organizational policies) facilitate or hinder your use of AI in your writing? How could support improve your confidence in writing?

4. Some instructors have concerns regarding originality or over-reliance on AI. Have you experienced this sort of ethics-related concern? In what way do ethics-related concerns affect your writing habits and self-efficacy?

5. How does your experience as a teacher inform your way of using AI tools? For example, do you tend to focus more frequently on checks for grammar, as a novice or high-level writing strategies, as an expert?

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