Generative AI Pragmatic Scaffolding and Interaction Effects on Oral Fluency in Saudi Arabia: Self-Regulation and Proficiency Roles

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Abstract

Oral fluency becomes a problem for Saudi EFL students with high foreign language speaking anxiety. Nevertheless, the mechanisms by which fluency and the quality of interactions can be influenced by a generative AI scaffold remain unclear. This study examined generative AI pragmatic scaffolding (GAPSC) and AI Interaction Effects (INTEFF) through the lens of their effects on oral fluency, with self-regulation as the mediating factor and language proficiency as the moderator. The study used a quantitative cross-sectional survey of 345 Saudi university students majoring in English. The data were analyzed using PLS-SEM. The results indicate that GAPSC and INTEFF can be used to predict oral fluency. Similarly, self-regulation played a mediating role in both relationships. Language proficiency negatively moderated the GAPSC fluency relationship and positively moderated the INTEFF fluency relationship. Theoretically, this study contributes to Sociocultural Theory (SCT) and Self-Regulated Learning (SRL) by synthesizing AI scaffolding, interaction effects, and self-regulation into a single fluency model. In practice, this study provides evidence-based recommendations from Saudi educators for creating proficiency-sensitizing AI-mediated support interventions that align with Vision 2030.

Keywords: Generative AI scaffolding; oral fluency; self-regulation; AI interaction effects; Saudi EFL learners

1. Introduction

The advent of Generative Artificial Intelligence (GenAI) in the academic environment has radically reshaped the English as a Foreign Language (EFL) learning process, particularly in Saudi Arabia. Despite the degree of technological progress, there is an even greater issue: Saudi EFL students are still struggling with oral fluency, which is typically characterized by high speaking anxiety (Alqahtani et al. 2026). Although GenAI might be adopted as a solution owing to access to automated feedback and simulated conversations, the quality and frequency of AI interactions differ for students, which might lead to unstable educational outcomes (Allehyani et al. 2025). Additionally, a theoretical problem concerns the indistinct relationship between the direct and indirect effects of Generative AI Pragmatic Scaffolding (GAPSC) on oral fluency (OFLU) in autodidactic scenarios (Bhar 2026). These tools are superficially used by many learners without the necessary self-regulatory mechanisms to internalize AI's linguistic output of AI (Yang, 2026). Consequently, systematic research into the integration of structured AI-mediated scaffolding to address the gap between passive tool use and the active growth of fluency in the Saudi higher-education sector is urgently needed (Almusharraf & Bailey, 2025). Furthermore, the paucity of empirical research on the interaction effects of AI engagement on oral production remains an important impediment to successful curriculum development and pedagogical innovation in this field.

Thus, the body of literature on general attitudes towards AI in education is already immense; however, there is a gap in the interaction effects of oral fluency in GenAI scaffolding. Existing literature has focused on writing support (Torres and Kahveci, 2025), vocabulary acquisition (Haruna et al., 2025a), and learners' attitudes (Yousef, 2026), while ignoring the subtle influence of pragmatic support on oral production. Although evidence exists that AI can be used to develop speaking skills (Tuan, 2026), the role of self-regulation (SR) as a mediating factor and the moderating impact of language proficiency (LPROF) have not been addressed in previous studies. This is illustrated by the fact that, even though Mohebbi (2025) also reports that AI can encourage learner independence, the mechanisms by which the quality of AI interaction (INTeff) leads to oral fluency (OFLU) remain under-theorized. In addition, the available empirical data are often incomplete. Further studies by Kooti et al. (2025) and Iftikhar et al. (2025) underscore the importance of stronger and more robust empirical evidence to confirm the effectiveness of AI-mediated speaking tasks in language learning in the future. This study aimed to test the effects of Generative AI Pragmatic Scaffolding and AI interaction on oral fluency among Saudi EFL learners, with the research question aimed at exploring the mediating role of self-regulation and the moderating role of language proficiency. The findings of this study can be applied to the theoretical framework as a whole on Human-AI interaction during language learning, setting a precedent for future research in the Middle East. Thus, this study contributes to the goals of Saudi Vision 2030, specifically in digital transformation and learning excellence, to enhance the communication skills of future Saudi graduates.

2. Literature Review and Theoretical Framework

The proposed theoretical framework (Figure 1) is based on (SCT) and (SRL). This offers a strong explanation of how AI-mediated learning enhances English oral proficiency. To strengthen the emphasis on large independent variables, SCT enables the classification of Generative AI Pragmatic Scaffolding (GAPSC) and AI Interaction Effects (INTEFF) as mediating instruments that support learners in building their abilities within the Zone of Proximal Development (Vygotsky, 1978). Self-regulation (SR) also functions as a mediator in the model, consistent with SRL theory, which argues that learning outcomes depend on how learners plan, monitor, and evaluate their cognition (Zimmerman, 2000). Language Proficiency is introduced as an appropriate moderator for accounting for differences among individuals, and its importance is underscored within SCT. Figure 1 illustrates how active contribution can be integrated with SCT's social mediation to produce a comprehensive model of learning that unifies cognition and SRL. This study extends earlier fragmented studies by empirically linking AI scaffolding, interaction quality, and internal control systems to oral fluency, thereby establishing a shared theoretical basis for AI-supported language acquisition (Yang, 2026).

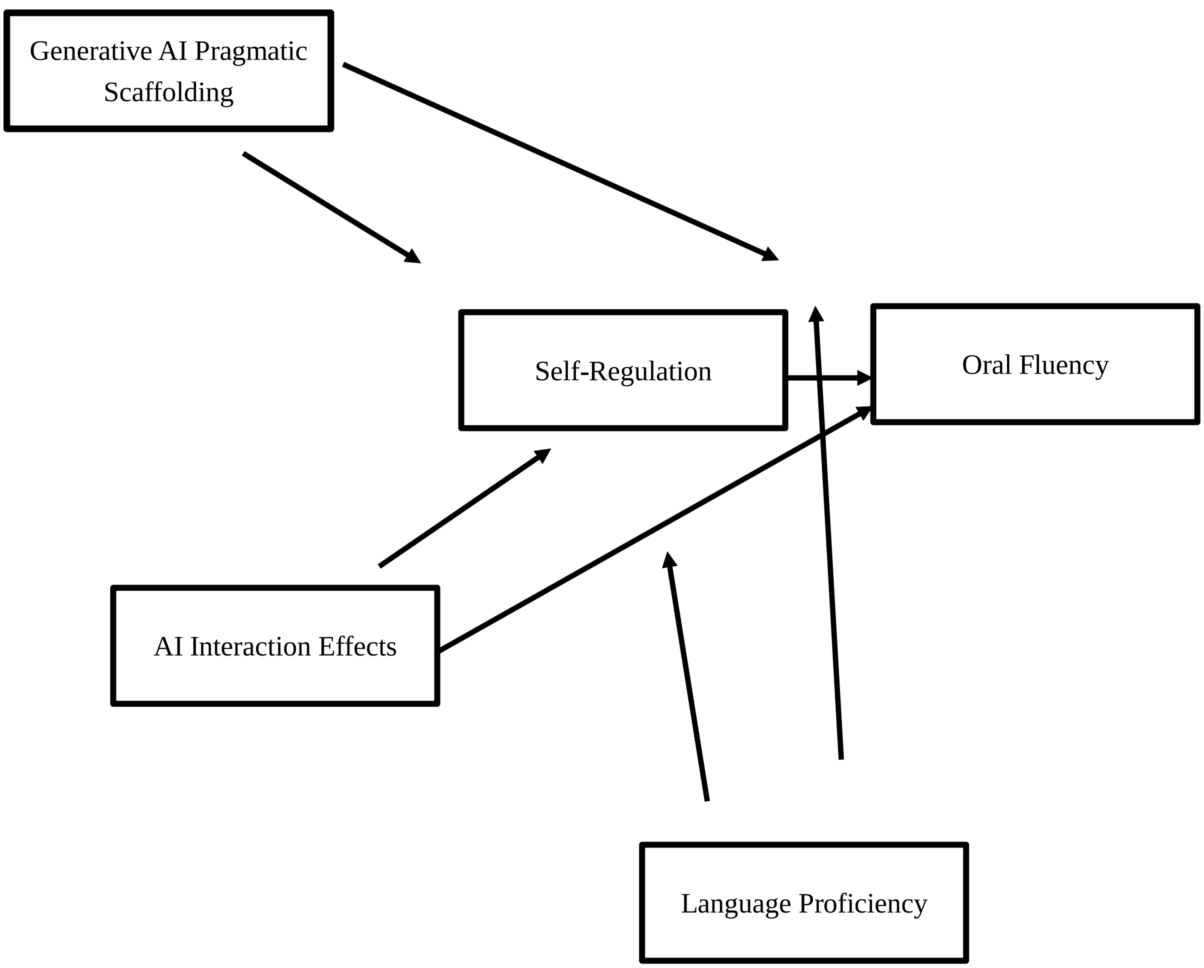

Figure 1. Research Model

3. Previous Studies and Hypothesis Development

Effect of Generative AI Pragmatic Scaffolding on Oral Fluency

Generative AI Pragmatic Scaffolding (GAPSC) in Teaching English as a Foreign Language (EFL) has drawn substantial attention for its impact on learners' oral fluency in recent years. Social Cognitive Theory (SCT) offers a useful theoretical basis for organizing exchanges among students, tools, and peers as they develop their skills. From this perspective, GAPSC can be understood as a support mechanism that instructs students through a structured method, which, in turn, broadens their abilities within the Zone of Proximal Development (ZPD). Recent studies have indicated that AI-mediated scaffolding improves speaking performance by providing tailored feedback and offering interactive practice materials. For example, Tuan (2026) found that AI-mediated practice is an effective scaffolding technology for enhancing speaking skills. Similarly, Bhar (2026) believed that AI-enhanced speech assessment and feedback software could effectively improve fluency and speaking performance in language learning. Moreover, another study by Chen et al. (2026) showed that oral language development was possible through interactive practice using Gen AI tools. Thus, ongoing dynamic support from the GAPSC can help learners overcome production obstacles and alleviate anxiety when using foreign language (Kooti et al., 2025). Consequently, this study proposes the following hypothesis:

H1: There is a statistically significant positive relationship between Generative AI Pragmatic Scaffolding and Oral Fluency.

Effect of AI Interaction Effects on Oral Fluency

AI interaction, including the frequency, quality, and interaction with AI gadgets, is a very important factor in developing oral fluency among EFL students, which can be effectively explained through the prism of Sociocultural Theory (SCT). According to SCT, learning is a social phenomenon, and interaction with more competent people, such as those using AI technology, can mediate language development. The important thing is not the exposure but the quality and nature of these interactions that help one gain oral fluency in the target language. Studies have shown that valuable interactions with AI tools can, on many occasions, be a significant input for the growth of speaking skill. Additionally, Aldaghri and Alshraah (2025) examined the pattern of use among Saudi university students who engaged in generative AI interactions and observed a positive correlation with AI language support. AI-delivered individualized interactive feedback (which may be customized) makes language rules easier to internalize and leads to more fluent speech (Kooti et al., 2025). Low-stakes settings and the adaptive, active nature of interactions between AI allow learners to engage in low-stakes interactions, which reduces anxiety and exposes them to more communicative practices. This concept aligns with the notion of collaborative learning suggested by SCT and the role of tools in the development of cognitive skills. AI's usefulness for oral proficiency is further evidenced by research showing improved fluency and pronunciation through AI-driven feedback systems (Bhar, 2026). Therefore, this study proposes the following hypothesis:

H2: There is a statistically significant positive relationship between AI Interaction Effects and Oral Fluency.

Effect of Generative AI Pragmatic Scaffolding on Self-Regulation

Generative AI Pragmatic Scaffolding (GAPSC) is also vital in the experience of self-regulation among English as a Foreign Language (EFL) students, which can be explained using Self-Regulated Learning (SRL) theory. SRL Theory highlights learners' personal involvement in managing their learning experiences, the use of goal-setting strategies, and self-monitoring. The GAPSC can significantly improve self-regulatory behaviors by offering structured and adaptive support. Recent research has shown that AI-based interactive support can positively affect the use of self-strategies and the involvement of EFL university students (Hwang, 2025). Additionally, as proposed by Tuan (2026), AI-supported practice may serve as a useful scaffold, unconditionally contributing to learners' growth in autonomy and control over the learning process. By providing personalized support, GAPSC helps learners plan, implement, and assess learning activities, thereby enhancing their self-regulatory capabilities (Alharbi, 2025). Therefore, the following hypothesis is proposed:

H3: A statistically significant positive relationship exists between Generative AI Pragmatic Scaffolding and Self-Regulation.

Effect of AI Interaction Effects on Self-Regulation

The self-regulation of EFL learners directly impacts their interaction with AI, including its frequency and interaction with AI tools. SRL Theory holds that learners drive their cognitive, motivational, and behavioral processes, which aid them in achieving their learning goals. Learners' self-regulation may be significantly affected by their interactions with AI tools. It has been found that AI-based corrective feedback (AIGFC) can forecast self-regulation in EFL situations, and thus, quality exchanges can improve self-regulation practices (Almayez, 2025). Nguyen (2024) found that AI-driven language-learning tools are beneficial for promoting learning because they foster engagement, a key factor in sustaining self-regulation. Another issue worth noting is the risk of overdependence on AI, as Chen et al. (2026) observed, which can hamper self-regulation unless it is addressed. Therefore, this study proposes the following hypothesis:

H4: There is a statistically significant positive relationship between AI Interaction Effects and Self-Regulation.

Effect of Self-Regulation on Oral Fluency

The Self-Regulated Learning (SRL) Theory posits that Self-Regulation (SR) is a key factor in the successful acquisition of language, especially in developing oral fluency in English as a Foreign Language (EFL). According to SRL Theory, learners who actively oversee their learning processes, goal-setting, strategy use, and self-monitoring of achievement reach greater heights of proficiency. Self-regulation is directly associated with the development and improvement of learners’ oral fluency. Previous studies have observed a positive correlation between self-regulated learning strategies and enhanced speaking ability. In addition, Almayez (2025) found that motivation and self-regulated learning strategies were related to English self-efficacy among Saudi EFL learners, as both enhanced their oral performance. This proactive learning style of goal-setting and self-monitoring is necessary to overcome difficulties in building spontaneous, coherent oral production in the epistemological language of the target language. Moreover, the ability to repair and make strategic corrections, which is fundamental to SRL, allows students to internalize language control and develop real-time speech production (Zhang 2024). Therefore, this study proposes the following hypothesis:

H5: There is a statistically significant positive relationship between Self-Regulation and Oral Fluency.

Mediating Effect of Self-Regulation on the Effect of Generative AI Pragmatic Scaffolding on Oral Fluency

The mediation of self-regulation (SR) between Generative AI Pragmatic Scaffolding (GAPSC) and Oral Fluency (OFLU) is a significant field of inquiry, especially through the lens of Sociocultural Theory (SCT). SCT highlights that cognitive development, which involves the acquisition of language, is a socially mediated process in which tools and interactions are important for learning. As an enabling instrument, the GAPSC offers systemic motivation that can foster learners'self-regulation to develop oral fluency. According to recent studies, AI-mediated feedback and scaffolding may enable learners to gain greater control over their learning and enhance their speaking ability. This efficiency in internalizing and practicing linguistic norms, which leads to greater oral fluency, is cultivated through the GAPSC model. In addition, the interaction between learners and AI tools (which can be understood as pragmatic scaffolding) influences learning processes, including self-regulation (Alharbi, 2025). Such mediation is compatible with the concept of scaffolding suggested by Vygotsky's Zone of Proximal Development. Thus, the following hypothesis was formulated:

H6a: Self-regulation mediates the effect of Generative AI Pragmatic Scaffolding on Oral Fluency.

Mediating Effect of Self-Regulation on the Effect of AI Interaction Effects on Oral Fluency

The mediating role of self-regulation (SR) in the association between Oral Fluency (OFLU), AI Interaction Effects (INTEFF), and Self-Regulation (SR) is a critical point to investigate within the framework of Sociocultural Theory (SCT). SCT is grounded in the view that learning is a social process, and that links with tools and more knowledgeable individuals foster cognitive development. The frequency, quality, and degree of interaction with AI can substantially influence a learner's self-regulatory processes, which, in turn, can affect oral fluency. Studies have shown that metacognitive control and self-monitoring capabilities can improve with interface quality, particularly in their ability to present AI-generated corrective feedback to learners (Aldaghri and Alshraah, 2025). Such enhanced self-regulation enables learners to better organize, implement, and assess their speaking practice, resulting in increased fluency. Such everlasting feedback on connection, self-observation, and readjustment, mediated by AI, is consistent with the tenets of SCT, as tools are viewed as extensions of human capabilities in the ZPD. Self-regulatory mechanisms are further empowered by the fact that AI can be tailored to meet each learner's needs and provide specific assistance, enabling learners to become more independent in their oral fluency acquisition (Almayez, 2025). Therefore, this study proposes the following hypothesis:

H6b: Self-regulation mediates the effect of AI interaction on oral fluency

H7a: Language Proficiency Moderates the Effect of Generative AI Pragmatic Scaffolding on Oral Fluency.

H7b: Language proficiency moderates the effect of AI interaction on oral fluency.

Moderating Effect of Language Proficiency on the Effect of Generative AI Pragmatic Scaffolding on Oral Fluency

Language Proficiency (LPROF) is expected to moderate the relationship between Generative AI Pragmatic Scaffolding (GAPSC) and Oral Fluency (OFLU), a dynamic that can be elucidated through Sociocultural Theory (SCT). SCT emphasizes the role of a learner's current knowledge and skills in mediating between them and new tools and learning environments.

Moderating Effect of Language Proficiency on the Effect of AI Interaction Effects on Oral Fluency

Nassar's (2026) study of AI-mediated feedback in instructing EFL learners in Saudi Arabia implicitly confirms that learners' initial proficiency levels mediate how they turn to and benefit from AI-driven interactive feedback. The importance of viewing learning proficiency as a moderating factor is evident in the effectiveness of AI-powered voice assistants in enhancing speaking skills, as discussed by Tang (2026). Therefore, this study proposes the following hypothesis:

4. Research Methodology

Research Instruments

The survey instrument comprised five items for each variable, adapted from previously validated scales. The items used to measure GAPSC were based on Park and Almusharraf (2025) and Bailey (2025) and were designed to support the functions of generative AI. The scale used to measure INTEFF was the Perceived Interactivity Scale developed by Wang and Zhang (2026). OFLU was assessed using a self-reported oral fluency scale, based on Guo (2025). Tseng et al. (2006) assessed SR at the level of evaluation through the task strategies dimension of the S2RLL scale. Finally, LPROF was evaluated using a self-perceived proficiency scale, which was a modified version of Al-Hoorie (2018). These items were measured on a five-point Likert scale, with the two extremes being strongly disagree and strongly agree. A five-point Likert scale was used because it provides a good balance of reliability, validity, and ease of use for respondents. It also offers better sensitivity and lower variance than 7-, 9-, or 10-point scales; however, it is less cognitively demanding and less fatiguing for symptom responses (Joshi et al., 2015). It also reduces scale mixing issues and enhances consistency in responses, especially in the context of education and cross-cultural interaction (Dawes, 2008; Revilla et al., 2014). A pilot study and pre-test of the instrument were conducted before the main data collection. Pulling et al. (2023) recommend pretesting, in which three specialists in applied linguistics reviewed the content of the pretest. After their comments, slight word modifications were made to achieve the required clarity and cultural fit for the questionnaire. Subsequently, 29 students were tested to check the internal consistency of the scales in a pilot study. The findings showed that each construct had a Cronbach's alpha coefficient above 0.70, validating the instrument's reliability (Brown et al., 2021).

Data Collection, Response Rate, and Data Analysis

Data were gathered through an online questionnaire administered to the target population. Of the 500 questionnaires that were distributed, 345 were considered valid and included in the analysis. The response rate was 69%, which is acceptable for conducting survey-based research in an educational context (Dhivyadeepa, 2015). The findings were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM). This approach is appropriate because it can account for mediation and moderation effects within a complex model without relying on strong assumptions regarding the normality of the data (Hair et al., 2019). Ethical approval for this research was collected by the Institutional Review Board Committee of the University (Approval No. SCBR-643/2026 (date of approval: February 2, 2026).

5. Results of the Study

The common method bias analysis using Harman's single-factor test is shown in Table 1. In the unrotated factor analysis, the first component explained 48.100% of the total variance, which is below the recommended 50% (Podsakoff et al. 2003). This indicates that common method bias is unlikely to be a significant threat to the validity of these findings. The first eigenvalue for the first component was 12.025, which was significantly larger than the eigenvalues of the subsequent components, but its explained variance was reasonable. Components one, two, three, four, and five explained 10.633%, 4.6597%, 2.980%, and 1.980% of the variance, respectively. The total variance explained by the five components was 70.646. These findings are consistent with Hair et al.'s (2019) approach to methodology, as it can be acknowledged that no single factor explains the variance in the dataset. Therefore, the measurement model can be considered resistant to common method bias, contributing to the dependability of the other structural equation modeling results. This finding is consistent with prior research on educational technology that employed similar diagnostic procedures (Alharbi, 2025).

Table 1. Common Method Bias

	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
Component	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	**12.025**	**48.100**	**48.100**	**12.025**	**48.100**	**48.100**	**6.733**	**26.933**	**26.933**
2	2.658	10.633	58.733	2.658	10.633	58.733	4.072	16.290	43.223
3	1.165	4.659	63.391	1.165	4.659	63.391	3.142	12.569	55.792
4	1.069	4.274	67.666	1.069	4.274	67.666	2.115	8.460	64.252
5	.745	2.980	70.646	.745	2.980	70.646	1.598	6.394	70.646

Table 2 presents the demographic characteristics of the 345 Saudi EFL participants. The age distribution shows that most (59.7%) are aged 18-22 and 23-27 (32.8%), indicating that they mostly consist of traditional undergraduates. The gender representation is 40.9 percent males and 59.1 percent females, indicating that female students are more represented in Saudi tertiary education (Ministry of Education, 2025). In terms of education, 80.9% were undergraduates and 19.1% were postgraduates. The research site is near equilibrium, as the percentages of English (49.9) and non-English majors (50.1) are closer, and thus more representative of the general population. The distribution of the years of study in the first and above years was quite balanced in this study. Self-rated English proficiency shows that 30.4% of the population are beginners, 51.0% are intermediate, and 18.6% are advanced, which implies that many participants have moderate and low oral fluency, in accordance with the practical problem identified by Alqahtani et al. (2026). Notably, 41.2 percentage of the respondents used AI tools daily, and 52.8 who had studied English 5-10 years ago, indicating that they had been exposed to English, but fluency remained a major concern. This profile attests to the relevance of this study in Saudi EFL environments (Almusharraf and Bailey 2025; Nassar 2026).

Table 2. Demographic Profile of the Respondents

Demographic Variable	Category	Frequency (n = 345)	Percent (%)
Age	18–22	206	59.7
	23–27	113	32.8
	28 and above	26	7.5
Gender	Male	141	40.9
	Female	204	59.1
Educational Level	Undergraduate	279	80.9
	Postgraduate	66	19.1
Field of Study	English Major	172	49.9
	Non-English Major	173	50.1
Year of Study	Year 1	83	24.1%
	Year 2	86	24.9
	Year 3	79	22.9
	Year 4 and above	97	28.1
English Proficiency (Self-rated)	Beginner	105	30.4
	Intermediate	176	51.0
	Advanced	64	18.6
Frequency of AI Tool Usage	Daily	142	41.2
	Weekly	102	29.6
	Monthly	61	17.7
	Rarely	40	11.6
Years of Learning English	Less than 5 years	63	18.3
	5–10 years	182	52.8
	More than 10 years	100	29.0

Table 3 presents the evaluation of the measurement model, indicating good psychometric characteristics for all five constructs. All factors had loadings between 0.783 and 0.865, which exceeded the recommended value of 0.70, indicating that all indicators captured the latent construct being measured (Hair et al. 2019). The alpha coefficients for the items varied between 0.875 and 0.887, exceeding the acceptable threshold of 0.70, thereby indicating internal consistency reliability. Composite reliability values (rho c) ranged from 0.909 to 0.917, while the rho a values ranged from 0.877 to 0.890; both sets of values were above the recommended levels and demonstrated strong construct reliability. Each construct's Average Variance Extracted (AVE) ranged from 0.668 to 0.690, which is well above the minimum convergence criterion of 0.50, thus supporting convergent validity. This finding aligns with earlier validations in AI-assisted language learning contexts (Park and Kim, 2025). The reliability results, along with the continued high scaling scores in 2020, indicate that the scales adapted for the Saudi EFL context are useful in the country and that the measurement model is well formulated, even prior to the structural equation analysis (Hair et al., 2019).

Table 3. Measurement Model

	Factor Loadings	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
AI Interaction Effects		**0.887**	**0.889**	**0.917**	**0.690**
INTEFF1	0.828				
INTEFF2	0.830				
INTEFF3	0.841				
INTEFF4	0.793				
INTEFF5	0.860				
Language Proficiency		**0.882**	**0.890**	**0.913**	**0.678**
LPROF1	0.829				
LPROF2	0.827				
LPROF3	0.812				
LPROF4	0.841				
LPROF5	0.808				
Oral Fluency		**0.875**	**0.877**	**0.909**	**0.668**
OFLU1	0.805				
OFLU2	0.783				
OFLU3	0.795				
OFLU4	0.865				
OFLU5	0.834				
Generative AI Pragmatic Scaffolding		**0.878**	**0.879**	**0.911**	**0.672**
GAPSC1	0.853				
GAPSC2	0.819				
GAPSC3	0.803				
GAPSC4	0.797				
GAPSC5	0.824				
Self-Regulation		**0.880**	**0.883**	**0.913**	**0.677**
SR1	0.818				
SR2	0.801				
SR3	0.823				
SR4	0.862				
SR5	0.807				

Table 4 shows the Heterotrait-Monomethod (HMT) ratio as a measure of discriminant validity. Each HTMT value between constructs was less than the conservative value (0.85) to ensure empirical separation between constructs (Henseler et al., 2015). The HTMT values for AI Interaction Effects and Self-Regulation (0.607) and Generative AI Pragmatic Scaffolding and Self-Regulation (0.487) were acceptable. The maximum value was between Self-Regulation and Oral Fluency at 0.708, which is still lower than 0.85. Oral fluency had an R-SQ of 0.555, indicating that this model accounted for 55.5% of the variation, whereas self-regulation had an R-SQ of 0.425. Oral fluency and self-regulation had Q-square predictive relevance values of 0.453 and 0.416, respectively (both above the null value), indicating a satisfactory predictive power (Hair et al., 2019). These findings align with those of prior PLS-SEM studies on AI-assisted language learning (Yang, 2026).

Table 4. Heterotrait-Monotrait (HTMT) Ratio Discriminate Validity

	R-square	Q-square	AI Interaction Effects	Generative AI Pragmatic Scaffolding	Language Proficiency	Oral Fluency	Self-Regulation	Language Proficiency x AI Interaction Effects	Language Proficiency x Generative AI Pragmatic Scaffolding
AI Interaction Effects									
Generative AI Pragmatic Scaffolding			0.137						
Language Proficiency			0.059	0.067					
Oral Fluency	0.555	0.453	0.575	0.506	0.234				
Self-Regulation	0.425	0.416	0.607	0.487	0.053	0.708			
Language Proficiency x AI Interaction Effects			0.114	0.040	0.027	0.054	0.076		
Language Proficiency x Generative AI Pragmatic Scaffolding			0.056	0.113	0.043	0.157	0.022	0.137	

The Value of the Variance Inflation Factor (VIF) used to measure multicollinearity is provided in Table 5. The VIFs are all significantly below the conservative threshold of 3.0, indicating no severe multicollinearity (Hair et al., 2019). In Oral Fluency, AI Interaction Effects depicted 1.447, Generative AI Pragmatic Scaffolding 1.279, and Self-Regulation 1.746; in the case of self-regulation, the predictors had a VIF rate of 1.015. The terms of the moderation interaction revealed VIF values of 1.037 and 1.038, respectively. These small values confirm that collinearity does not affect the estimation of the structural model, as recommended in the PLS-SEM literature (Hair et al., 2019).

Table 5. VIF

	Oral Fluency	Self-Regulation
AI Interaction Effects	1.447	1.015
Generative AI Pragmatic Scaffolding	1.279	1.015
Self-Regulation	1.746	nil
Language Proficiency x AI Interaction Effects	1.037	nil
Language Proficiency x Generative AI Pragmatic Scaffolding	1.038	nil

Table 6 presents the model fit based on PLS-SEM fit indices. The saturated and estimated models had standardized root mean square residuals of 0.047 and 0.048, respectively, which are below the recommended value of 0.08; therefore, the model fit was acceptable (Hu and Bentler, 1999). The Normed Fit Index (NFI) has the values were 0.899 and 0.898, close to the traditional threshold of 0.90. The d_ULS (0.715 vs. 0.741) and d_G (0.250 vs. 0.253) values showed minimal discrepancies between models. Chi-square values are 499.252 and 505.209. All fit indices indicate that the model developed based on the hypotheses satisfactorily captured the empirical data (Hair et al., 2019).

Table 6. Model Fit

	Saturated model	Estimated model
SRMR	0.047	0.048
d_ULS	0.715	0.741
d_G	0.250	0.253
Chi-square	499.252	505.209
NFI	0.899	0.898

The path coefficients of the five direct hypotheses are presented in Table 7 and Figure 2, respectively. H1 examined the relationship between Generative AI Pragmatic Scaffolding (GAPSC) and Oral Fluency (OFLU), showing a significant positive effect ($\beta = 0.221$, $t = 5.176$, $p < 0.001$, CI: 0.137 to 0.303). So, H1 is supported. An f-square of 0.086 is considered to be small. However, this relationship is statistically significant, as the f-square captures the added explanatory power of a certain predictor rather than the significance of the path coefficient (Hair et al., 2019). Even when the confidence interval of the relationship is not zero, the relationship is theoretically significant, even with a small F-squared value. This is consistent with Bhar (2026) and can be described by Sociocultural Theory (SCT), in which GAPSC is also an instrument of mediation in this Zone of Proximal Development, increasing learners' oral production abilities with categorical assistance. H2 tested the effect of AI Interaction Effects (INTEFF) on OFLU, yielding a significant positive effect ($\beta=0.292$, $t=6.382$, $p<0.001$, CI: 0.202 to 0.379), supporting H2. The f-square 0.132 indicates a small-to-medium effect size. SCT interprets this observation by suggesting that meaningful and frequent engagement with AI tools mediates cognitive growth, allowing learners to acquire linguistic norms by practicing low-pressure communicative practice, in line with Kooti et al. (2025). H3 examined the effect of GAPSC on Self-Regulation (SR), showing a significant effect (β=0.371, t=9.304, p<0.001, CI: 0.294 to 0.449), supporting H3 with a medium f-square of 0.236. This result can be explained within the framework of Self-Regulated Learning (SRL) Theory, because GAPSC provides personal feedback, allowing learners to monitor progress and adjust strategies to achieve it, as Hwang (2025) illustrates. [insert citation] H4 tested the INTEFF on SR (β=0.493, t=13.135, p<0.001, CI: 0.417 to 0.563), supporting H4 with a large f-square of 0.416. SRL Theory asserts that excellent AI interaction positively influences metacognitive regulation, allowing learners to gain greater control over learning activities (Almayez, 2025). H5 examined the SR on OFLU (β=0.382, t=7.970, p<0.001, CI: 0.286–0.476), supporting H5 with a medium f-square of 0.188.SRL theory explains that self-regulatory behaviors enable learners to identify their weaknesses and seek appropriate practice opportunities, thereby directly improving spontaneous oral production.

Table 7. Path Coefficients Results

Hypotheses	Path Analysis	Beta	Standard deviation	T statistics	2.5%	97.5%	f^2	P values	Decision
H1	Generative AI Pragmatic Scaffolding -> Oral Fluency	0.221	0.043	5.176	0.137	0.303	0.086	0.000	Supported
H2	AI Interaction Effects -> Oral Fluency	0.292	0.046	6.382	0.202	0.379	0.132	0.000	Supported
H3	Generative AI Pragmatic Scaffolding -> Self-Regulation	0.371	0.040	9.304	0.294	0.449	0.236	0.000	Supported
H4	AI Interaction Effects -> Self-Regulation	0.493	0.037	13.135	0.417	0.563	0.416	0.000	Supported
H5	Self-Regulation -> Oral Fluency	0.382	0.048	7.970	0.286	0.476	0.188	0.000	Supported

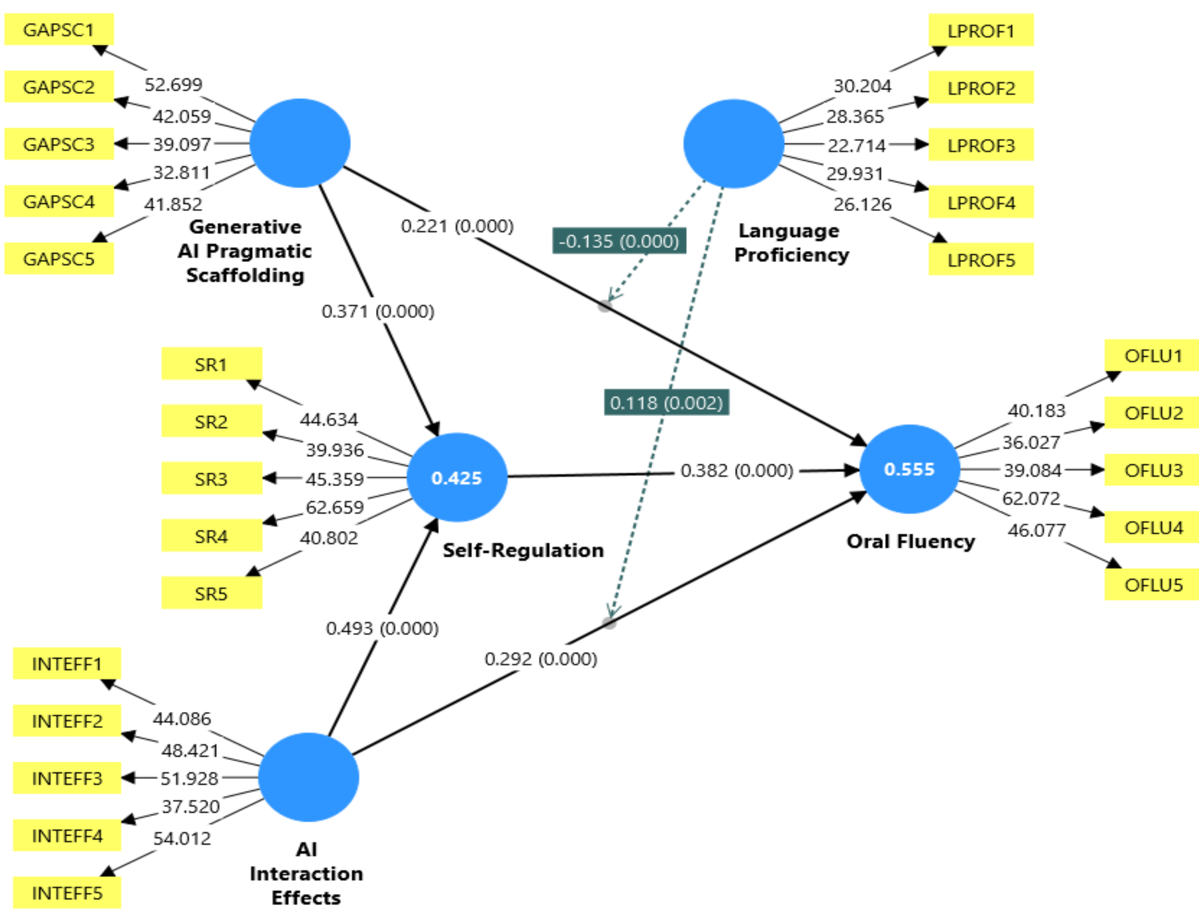

Figure 2. Graphical Path Coefficients Results

Table 8 presents the mediation analysis using an indirect approach. H6a suggested that self-regulation mediated the influence of Generative AI Pragmatic Scaffolding on Oral Fluency, which had a strong indirect effect (β=0.142, t=6.046, p<0.001, CI: 0.099–0.189). H6a is, therefore, supported. The effect size, although not reported as f-squared for indirect paths, is significant because the confidence interval does not include the value of zero. This mediation aligns with that of Nassar (2026), who found that feedback in AI-mediated interventions supported self-regulated learning and speaking fluency. According to Sociocultural Theory (SCT), the GAPSC can be described as a mediational tool that initially increases learners' self-regulatory capacity, which then transfers to oral fluency through internalization in the Zone of Proximal Development. H6b proposed that self-regulation mediates the effect of AI Interaction Effects on Oral Fluency, showing a significant indirect effect (β=0.188, t=6.790, p<0.001, CI: 0.136 to 0.244), supporting H6b. This finding is explained by Self-Regulated Learning (SRL) Theory, because quality AI interactions contribute to the development of metacognitive regulation and self-monitoring skills, and subsequently, to learners' ability to plan and evaluate their speaking practice, becoming more effective (Nguyen, 2024).

Table 8. Mediation Analysis Using the Indirect Method

Hypotheses	Path Analysis	Beta	Standard deviation	T statistics	2.5%	97.5%	P values	Decision
H6a	Generative _AI Pragmatic _Scaffolding -> Self-Regulation -> Oral Fluency	0.142	0.023	6.046	0.099	0.189	0.000	Supported
H6b	AI _Interaction _Effects -> Self-Regulation -> Oral Fluency	0.188	0.028	6.790	0.136	0.244	0.000	Supported

The results of the moderation analysis are presented in Table 9. H7a tested whether Generative AI Pragmatic Scaffolding had a significant negative interaction with Language Proficiency (H7a: -0.135, t=3.549, p=0.001, CI: -0.208 -0.059). The f-square of 0.040 indicates a small effect size in this study. However, the relationship is significant because the f-square quantifies the unique variance of the interaction term, which is usually small in moderation tests (Hair et al., 2019). Figure 3 indicates that GAPSC improves oral fluency more significantly among learners with lower proficiency than it does among those with higher proficiency. Sociocultural Theory (SCT) holds that scaffolding is more helpful for lower-proficiency learners, as they are placed in a larger Zone of Proximal Development and need organizational support (Tuan, 2026). H7b hypothesized a positive interaction between AI Interaction Effects and Oral Fluency, which Language Proficiency moderates. The interaction (β=0.118, t=3.050, p=0.002, CI: 0.040 to 0.191) was significant. However, the f-square value was small (0.032).

Table 9. Moderation Analysis Results

Hypotheses	Path Analysis	Beta	Standard deviation	T statistics	2.5%	97.5%	f^2	P values	Decision
H7a	Language Proficiency x Generative AI Pragmatic Scaffolding -> Oral Fluency	-0.135	0.038	3.549	-0.208	-0.059	0.040	0.000	Supported
H7b	Language Proficiency x AI Interaction Effects -> Oral Fluency	0.118	0.039	3.050	0.040	0.191	0.032	0.002	Supported

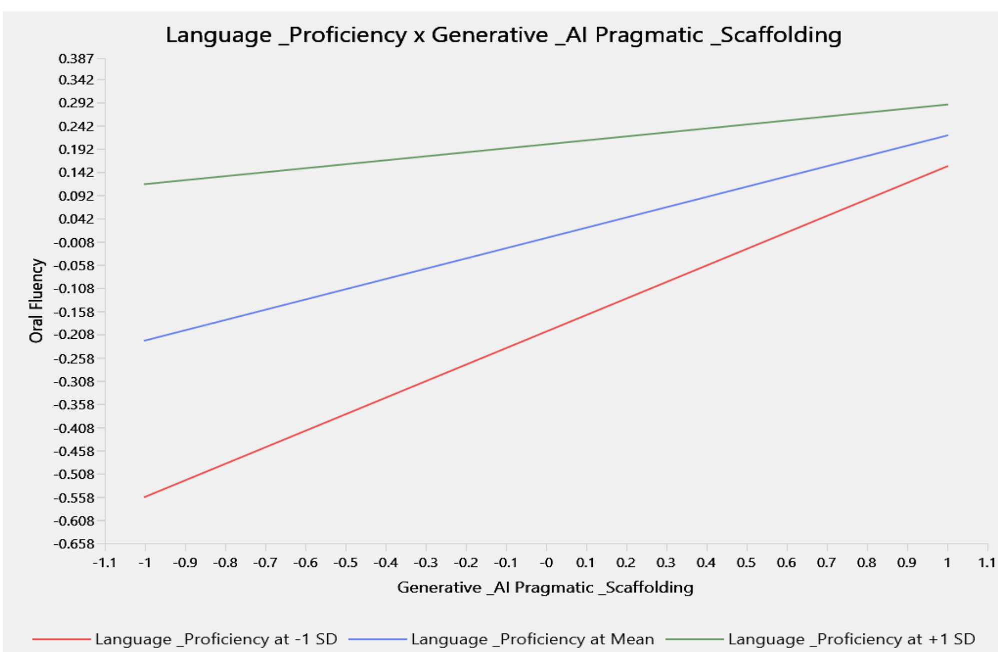

Figure 3. Moderation Effect of LPROF on GAPSC and OFLU

Figure 3. Interaction plot depicting the moderating effect of language proficiency (LPROF) on the association between Generative AI Pragmatic Scaffolding (GAPSC) and oral fluency (OFLU). The three lines represent participants at low (−1 SD), mean, and high (+1 SD) levels of language proficiency, demonstrating that increased proficiency enhances the positive impact of AI scaffolding on oral fluency outcomes.

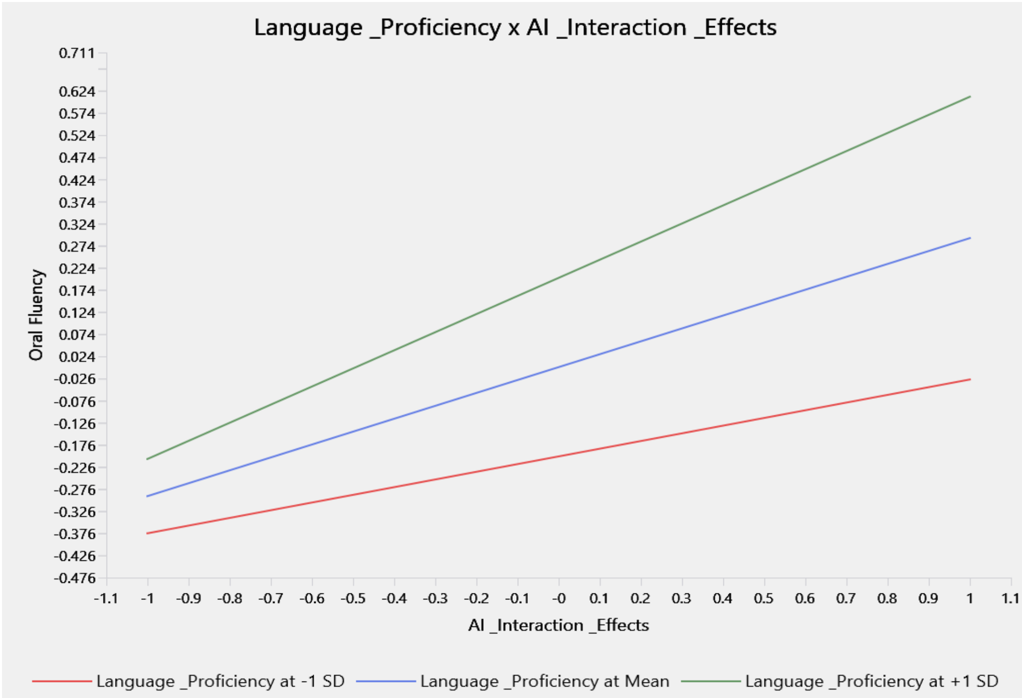

Figure 4. Moderation Effect of LPROF on INNEFF and OFLU

Figure 4 shows an interaction plot illustrating the moderating influence of language proficiency (LPROF) on the relationship between AI Interaction Effects (INNEFF) and oral fluency (OFLU). The three lines correspond to participants with low (−1 SD), mean, and high (+1 SD) levels of language proficiency, indicating that proficiency level differentially affects the influence of AI interaction on oral fluency.

6. Discussion of the Study

This study investigated the direct, mediating, and moderating relationships, all of which have empirical support. Concerning the direct effects, Hypothesis 1 (H1) was validated by the finding that Generative AI Pragmatic Scaffolding positively affects Oral Fluency. This result aligns with Bhar's (2026) research, which demonstrated that AI-assisted practice serves as scaffolding support for the enhancement of oral skills, and that GenAI tools can facilitate oral language development through interactive engagement. This relationship can be understood through Sociocultural Theory: instead of the GAPSC mediational tool, AI-guided support functions within the learner's Zone of Proximal Development, enabling language production that the learner cannot independently achieve through structured and adaptive assistance (Vygotsky, 1978). Similarly, the positive impact of AI Interaction Effects on Oral Fluency, supporting Hypothesis 2 (H2), corresponds with Alharbi (2025), who emphasized the significance of meaningful interactions with AI tools, and Kooti et al. (2025), who provided evidence that interactive feedback aids learners in internalizing linguistic norms. Within the framework of SCT, when a learner engages repeatedly with high-quality AI, this process can be considered social mediation, whereby the learner internalizes linguistic norms through frequent practice in low-stakes interactions with the AI.

The positive impact of GAPSC on Self-Regulation, as shown in H3, is consistent with Hwang (2025), who also found that AI-empowered support leads to increased use of self-regulation strategies and greater engagement. This outcome can be described by the Self-Regulated Learning Theory, which predicts that individualized AI feedback helps learners become aware of their progress and can lead them to vary their strategies (Zimmerman, 2000). Similarly, the positive correlation between INTEFF and Self-Regulation, which supports H4, aligns with Almayez's (2025) findings that AI-generated corrective feedback predicts self-regulation and with Aldaghri and Alshraah's (2025) finding that AI-based feedback forecasts metacognitive control. According to SRL Theory, effective interactions foster quality, leading to greater metacognitive awareness and enabling learners to gain greater control over learning processes (Zhang, 2024). Lastly, the positive self-regulation effect on Oral Fluency, supporting H5, is consistent with Sánchez et al. (2023), who showed that a self-evaluation procedure has a direct positive effect on speaking performance. According to SRL Theory, learners are more prepared to overcome their speaking issues by actively setting goals and tracking their performance.

The reports that self-regulation mediates the GAPSC-Oral fluency relationship to support H6a are an extension of the works provided by Nassar (2026), pointing to the role of AI-mediated feedback in facilitating self-regulated learning and speaking fluency, and Alharbi (2025), raising the observation that the use of AI tools affects self-regulation. Likewise, the presence of self-regulation mediating the

INTEFF-Oral Fluency relationship to support H6b aligns with Aldaghri and Alshraah (2025), who showed that AI interactions elevate metacognitive regulation, and Nguyen (2024), who underscored that AI-mediated devices facilitate engagement that is essential for self-regulation. This mediation may be especially effective for learners who frequently and substantially interact with AI feedback loops, enabling self-monitoring and strategic fine-tuning through continuous engagement and adaptation to AI feedback (Bhar, 2026).

Regarding moderation, the negativity of Language Proficiency as a moderator in GAPSC-Oral Fluency (H7a) supports the idea that moderation can be successful, but it does not meet easy beliefs. This negative moderation effect occurs when scaffolding is most helpful to beginning learners because they lack the inner resources that more advanced learners have to self-regulate their learning process. On the other hand, the positive interaction of language proficiency with the INTEFF-Oral Fluency relationship that confirmed H7b supports Haruna et al. (2025a), who discovered that proficiency levels moderate the effect of the AI interaction, and Tang (2026), who emphasized the role of proficiency as a mediating variable in AI-enhanced speaking practice. Higher-proficiency learners have the linguistic resources to engage in more complex interactions in AI practice and receive advanced feedback. In contrast, lower-proficiency learners might find some interactions confusing or overly complicated to address their needs (Kooti et al., 2025). Such positive moderation is evident when learners possess adequate basic competence to optimize their use of interactive feedback and engage in more advanced communication.

7. Implications

This study has several theoretical implications. It also builds upon Sociocultural Theory by showing that Generative AI Pragmatic Scaffolding is a valid tool of mediation within the Zone of Proximal Development, but that it extends beyond the bounds of human interaction by mediating between humans and AI. The findings presented above inform practitioners that AI tools cannot be adopted without first satisfying the premises fabricated by the integrated model, guided by curriculum designers, and based on systematic scaffolding plans. Before learners can achieve fluency in interacting with AI, teachers need to teach them self-control measures. Negative moderation also implies that scaffolding levels need to be reduced as learners become more proficient to avoid excessive scaffolding that may inhibit the development of independent production. Practically, the study can provide relevant solutions for planning interventions that both consider and differentiate the intensity of AI scaffolding according to the learner's ability, with less able learners receiving greater scaffolding and highly able learners receiving less, as this leads to more effective acquisition of fluency in many cases. Saudi Vision 2030 is also supported by research, which shows that the potential of digital transformation to improve the communication competence of graduates can positively affect speaking anxiety and employability rates in a world of less globalization.

8. Conclusion

The results of this study clearly show that Generative AI Pragmatic Scaffolding and AI Interaction Effects should be used to enhance oral fluency in Saudi EFL learners and that self-regulation is a key mediating variable. Practically, there is a paradigm shift in EFL instruction, whereby teachers create proficiency-responsive AI interventions that directly build self-regulatory skills rather than relying solely on oral practice. It is concluded that generative AI, when strategically designed and aligned with self-knowing, existential competencies, and skills, has the transformative potential to address current challenges in oral fluency and will ultimately support the objectives of digital transformation and the attainment of Saudi Vision 2030 in education.

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Author contributions

Dr. S. M.A. and Dr. W. A. A. were responsible for the study design and revision. Dr. S. A. was responsible for data collection. Dr. L. H. R. A. drafted the manuscript, and Dr. S. M.A. revised it. All authors have read and approved the final manuscript.

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Competing interests

The authors declare that they have no competing financial interests or personal relationships that could have influenced the work reported in this study.

Informed consent

Participation was voluntary, and informed consent was obtained before data collection.

Ethics approval

Ethical approval for this study was granted by the Institutional Review Board Committee of Prince Sattam bin Abdulaziz University (Approval No. SCBR-642/2026 (date of approval: February 1, 2026).

Provenance and peer review

Not commissioned; externally double-blind, peer-reviewed.

Data availability statement

The data supporting the findings of this study are available upon request from the corresponding author. The data are not publicly available because of privacy or ethical restrictions.

Data sharing statement

No additional data were available.

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