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Research article

# Artificial Intelligence Coaching for Confident Speaking and Spontaneous Argumentation

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## Abstract

Artificial intelligence is increasingly used to support spoken language practice. However, different AI-assisted support systems do not support learners' confidence equally. This explanatory sequential mixed-methods study examines associations among the perceived usefulness of AI feedback, AI-mediated argumentative scaffolding, self-reported cognitive engagement, and speaking self-efficacy in the context of spontaneous argumentation. The quantitative phase involved 130 university EFL learners who had used an AI-assisted argumentation coaching application for at least eight weeks. Regression analysis showed that perceived usefulness of AI feedback was positively associated with so-called speaking self-efficacy, that is, the confidence to perform spoken tasks successfully ($\beta$ = .410, $p$ < .001), as was AI-mediated argumentative scaffolding ($\beta$ = .248, $p$ = .002). In contrast, self-reported cognitive engagement was not significantly associated with speaking self-efficacy after the other predictors were taken into account ($\beta$ = −.028, $p$ = .725). The qualitative phase involved eight purposively selected participants representing variation in gender, year of study, IELTS target, and experiences relevant to the quantitative patterns. Thematic analysis of semi-structured interviews identified three explanatory themes: structural scaffolding, psychological safety, and cognitive limits. Participants frequently described organizational guidance and a nonjudgmental practice environment as useful, while some also reported repetition, fatigue, and dependence during extended AI use. Integrating the two phases suggests that perceived usefulness, scaffolding, and cognitive engagement should not be treated as interchangeable dimensions of AI-assisted speaking practice. The study proposes a provisional cognitive-threshold hypothesis for future testing, but does not claim a causal or nonlinear effect. The findings support strategically designed AI-assisted speaking practice that maintains opportunities for independent reasoning and human interaction.

**Keywords:** Artificial intelligence; Speaking self-efficacy; Spontaneous argumentation; Cognitive engagement; Instructional scaffolding; English as a foreign language; IELTS

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Научная статья

# Коучинг с искусственным интеллектом для уверенного говорения и спонтанной аргументации

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**Аннотация**
Искусственный интеллект всё активнее используется для поддержки устной языковой практики, однако разные формы такой поддержки могут по-разному соотноситься с уверенностью обучающихся. В исследовании с последовательным объяснительным смешанным дизайном изучались связи между воспринимаемой полезностью обратной связи от искусственного интеллекта, аргументативным скаффолдингом, когнитивной вовлечённостью и самоэффективностью говорения в контексте спонтанной аргументации. В количественном этапе участвовали 130 студентов, изучающих английский как иностранный язык и использовавших приложение с искусственным интеллектом не менее восьми недель. Регрессионный анализ выявил положительные связи самоэффективности с воспринимаемой полезностью обратной связи ($\beta = .410$, $p < .001$) и аргументативным скаффолдингом ($\beta = .248$, $p = .002$). Когнитивная вовлечённость не показала статистически значимой связи после учёта других предикторов ($\beta = -.028$, $p = .725$). В качественном этапе участвовали восемь целенаправленно отобранных респондентов. Тематический анализ полуструктурированных интервью выявил три темы: структурный скаффолдинг, психологическую безопасность и когнитивные ограничения. Участники отмечали полезность организационной поддержки и неосуждающей среды, но некоторые сообщали о повторяемости обратной связи, утомлении и зависимости при длительном использовании искусственного интеллекта. Интеграция двух этапов показывает, что воспринимаемую полезность, скаффолдинг и когнитивную вовлечённость не следует считать взаимозаменяемыми аспектами практики. Исследование предлагает предварительную гипотезу когнитивного порога для последующей проверки, не утверждая наличие причинного или нелинейного эффекта. Результаты поддерживают стратегически организованное использование искусственного интеллекта при сохранении самостоятельного рассуждения и взаимодействия с человеком.

**Ключевые слова:** Искусственный интеллект; Самоэффективность говорения; Спонтанная аргументация; Когнитивная вовлечённость; Педагогический скаффолдинг; Английский как иностранный язык; IELTS

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## INTRODUCTION

In today's increasingly globalized system of higher education and professional mobility, English proficiency continues to play a decisive role in academic and career advancement. In this competitive environment, high-stakes exams such as the International English Language Testing System (IELTS) often determine access to universities and immigration pathways. Among its components, IELTS Speaking Part 3 is widely regarded as one of the most demanding. It requires candidates to engage in abstract discussion, speculate on complex issues, and construct well-reasoned arguments under strict time limits (Fernandez, 2018).

Unlike Parts 1 and 2, which focus on personal experiences and descriptions, Part 3 requires learners to synthesize ideas, develop counter-arguments, and use advanced sentence structures spontaneously. For many EFL learners, the difficulty goes beyond vocabulary or grammar. The real challenge lies in organizing ideas coherently and sustaining argumentative depth in real time.

Traditional language classrooms often struggle to provide the kind of individualized and immediate feedback needed to develop this level of skill. Large class sizes and limited speaking time mean that students rarely receive detailed, one-on-one guidance on how to structure and refine their arguments (Richards, 2015; Wang, 2014). As a result, many learners experience high levels of speaking anxiety, which can significantly undermine their confidence and performance.

Speaking self-efficacy refers to a learner's belief in their ability to perform spoken tasks successfully (Bandura, 1997). This belief plays a key role in shaping their willingness to communicate, their persistence when communication breaks down, and ultimately their overall speaking performance. In recent years, AI-based programs and chatbots have become increasingly prominent in educational practice (Chiu et al., 2024). AI-powered conversational tools and automated evaluation systems now offer personalized, on-demand speaking practice. These systems can provide immediate feedback on pronunciation, grammar, and, increasingly, the coherence and depth of spoken arguments.

By creating a low-pressure environment, AI-assisted practice may help learners overcome the fear of negative evaluation that often limits participation in traditional EFL classrooms. This is especially relevant in contexts where students hesitate to speak due to social or cultural expectations (Cheng, 2000). Although these tools are spreading rapidly across educational settings, research on their influence on higher-order cognitive skills is still at an early stage.

A clear gap remains in the literature. While research on AI-assisted speaking examined performance, feedback, confidence, and anxiety, the relationship between AI-assisted scaffolding and spontaneous argumentative speaking remains less clearly understood, particularly in the cognitively demanding context of IELTS Speaking Part 3. The present study therefore focuses not on whether AI is generally beneficial, but on whether different dimensions of learners' AI-assisted practice – perceived usefulness, argumentative scaffolding, and self-reported cognitive engagement – show distinct relationships to speaking self-efficacy, and how learners explain those patterns in relation to perceived argumentative performance. Although interaction with non-human agents

may create a sense of psychological safety, the relationship among sustained AI feedback, cognitive engagement, and speaking self-efficacy remains insufficiently understood.

This situation presents a tension. On the one hand, AI-based scaffolding may provide structural support for developing and organizing arguments. On the other hand, heavy reliance on generative AI for ideas, transitions, or argument structure may be accompanied by cognitive offloading, repetition, or dependency. These possibilities suggest that perceived usefulness, argumentative scaffolding, and cognitive engagement should not be assumed to operate in the same way or to exhibit identical relationships with speaking confidence.

To address this gap, the present study adopts an explanatory sequential mixed-methods design to examine relationships among learners' perceptions of AI-assisted argumentation coaching, cognitive engagement, and speaking self-efficacy. Its contribution lies in bringing these dimensions together within spontaneous IELTS-style argumentation rather than treating AI-assisted speaking practice as a single undifferentiated experience. The quantitative phase examines whether perceived usefulness of AI feedback (PUAF), AI-mediated argumentative scaffolding (AMAS), and self-reported cognitive engagement with AI (CEAI) show different associations with speaking self-efficacy (SSE). The qualitative phase uses thematic analysis of semi-structured interview data to provide contextual explanations for the quantitative patterns. Given the cross-sectional design, the quantitative findings are interpreted as associations rather than causal effects.

The study is guided by two research questions. RQ_1 (Quantitative): How are perceived usefulness of AI feedback, AI-mediated argumentative scaffolding, and cognitive engagement with AI associated with learners' speaking self-efficacy? RQ_2 (Qualitative): How do learners describe their experiences of AI feedback, scaffolding, and cognitive engagement in relation to speaking confidence and perceived argumentative performance?

## LITERATURE REVIEW

The theoretical and empirical foundations of this study lie at the intersection of cognitive load theory (Sweller et al., 2011), sociocultural perspectives on scaffolding, and the psychology of language learning. Bringing artificial intelligence into educational settings calls for a careful rethinking of how learners process information, build knowledge, and develop self-regulatory beliefs in highly digital and algorithm-driven environments.

### AI-Mediated Argumentative Scaffolding and Critical Thinking

The concept of scaffolding originates from Lev Vygotsky's (1978) theory of the Zone of Proximal Development, which suggests that learners can reach higher levels of thinking when they receive structured and temporary support from a more capable peer or instructor. In today's educational context, generative AI tools are increasingly taking on this supportive role.

Recent research highlights the potential of AI to provide clear structural guidance that strengthens critical thinking. For example, Huanhuan Zhang et al. (2025) found that postgraduate learners using ChatGPT for IELTS speaking practice reported increased practice engagement and perceived support for English-speaking development, alongside a significant association between regular interaction and grammar improvement. In a similar vein, Hui Hong et al. (2025) found that integrating generative AI into a carefully designed pedagogical framework enhanced cognitive engagement and promoted deeper analytical thinking among EFL learners.

However, extending this type of scaffolding from writing tasks to spontaneous speaking faces considerable cognitive challenges: spoken argumentation, particularly in IELTS Speaking Part 3, requires real-time processing, quick access to vocabulary, and rapid organization of ideas (Skehan, 2009). Yonggang Sun and Yinfang Wu (2026) examined the effectiveness of AI-supported scaffolding in tertiary EFL settings using the Technology Acceptance Model alongside Cognitive Load Theory. Their results show that perceived usefulness and perceived ease of use of AI tools are predictors of learning efficiency. More importantly, their structural equation modeling indicates that the frequency of AI interaction influenced outcomes mainly through deeper cognitive processing (Sun & Wu, 2026). In other words, AI support was most beneficial when it pushed learners to think actively, rather than simply accept automated feedback.

In the context of spoken argumentation, AI systems that prompt learners to consider counter-arguments or apply logical frameworks can function as cognitive supports that expand their range of argumentative strategies.

**Psychological Safety, Anxiety Reduction, and Speaking Self-Efficacy**

The emotional side of language learning is just as important as the cognitive one, especially when learners aim to develop advanced speaking skills. Foreign language speaking anxiety remains a common barrier. It raises the affective filter and limits learners' ability to process input effectively (Krashen, 1982). In the context of remote teaching in emergency situations, Marco Cancino and Gonzalo Cabello (2024) reported high levels of both foreign-language speaking anxiety and computer self-efficacy but found no statistically significant correlation between the two; their qualitative findings nevertheless identified several contextual and technology-related factors shaping speaking anxiety. AI conversational agents introduce a markedly different psychological setting, one that may further reshape this relationship.

In the Vietnamese context, Quang Nhat Nguyen et al. (2025) reported a significant positive correlation between frequent AI-supported speaking practice and learners' self-reported confidence. Wei Zhou (2023) proposed that integrating ChatGPT with voice-assistant functionality could support oral, chat-based constructive communication for EFL learners. Likewise, Cennet Yildiz (2024) examined ChatGPT as a virtual speaking tutor and concluded that it strengthened EFL learners' speaking self-efficacy by offering interactive practice in a nonjudgmental space.

A systematic review by Lujie Huang and Ming Liu (2025), which synthesized studies published between 2004 and 2024, reached a similar conclusion. The authors argued that educational technology tends to reduce foreign language anxiety by creating

a sense of psychological safety. Because human–computer interaction often involves anonymity and minimal social evaluation, learners feel freer to experiment with complex grammar and advanced vocabulary without fearing criticism from teachers or peers.

This supportive environment aligns closely with Albert Bandura's (1997) theory of self-efficacy. According to this framework, mastery experiences and reduced physiological stress are two major sources of self-efficacy. When learners can practice repeatedly, make mistakes, and try again without embarrassment, they accumulate successful experiences. In this way, AI-assisted coaching may be associated with stronger speaking self-efficacy, particularly when learners perceive the practice environment as less judgmental and experience a sense of progress.

### Cognitive Engagement, Offloading, and Possible Limits of AI Support

Although structural scaffolding and psychological safety offer benefits, a growing body of research cautions against the cognitive risks of overusing artificial intelligence in education. Michael Gerlich (2025) provides insight into the concept of cognitive offloading in AI-supported learning. His study found a significant negative correlation between frequent AI use and critical thinking ability. When learners rely heavily on instant, machine-generated answers, they may engage less in the active reasoning required for deeper evaluation. While offloading tasks to AI can temporarily reduce the burden on working memory, outsourcing complex thinking may weaken cognitive resilience and limit long-term retention (Risko & Gilbert, 2016).

This creates a paradox in AI-assisted language learning. Early interaction with AI can supply scaffolding and increase learners' confidence. However, prolonged dependence may lead to diminishing returns. If learners consistently rely on AI to generate ideas, structure arguments, and suggest vocabulary, they may bypass the deep processing essential for genuine language development and independent critical thinking. As Hoang Nguyen Huu (2025) argues, even though AI tools can improve performance-related aspects such as fluency and pronunciation, sustained cognitive engagement remains the core mechanism of meaningful language acquisition.

These concerns suggest that greater engagement with AI should not automatically be assumed to correspond to stronger speaking confidence. For spontaneous argumentative speaking, structural scaffolding, perceived usefulness, and cognitive engagement may represent related but distinct dimensions of AI-assisted practices. The present study therefore examines these dimensions separately without assuming that greater engagement necessarily corresponds to stronger speaking self-efficacy but uses qualitative follow-up data to interpret the relationship to speaking self-efficacy.

## METHODOLOGY

To examine the complex relationship between AI feedback, cognitive processing, and learners' affective factors, this study adopted an explanatory sequential mixed-methods design (Creswell & Plano Clark, 2018). This approach involved two stages. First, quantitative data were collected and analyzed to identify general patterns and

relationships. Then, a qualitative phase followed to clarify, expand, and add contextual depth to the initial statistical findings.

**Quantitative Phase: Participants and Procedures**

The quantitative phase estimated a regression model in which Speaking Self-Efficacy (SSE) served as the dependent variable. The sample included 130 university EFL students who were preparing for the IELTS exam. To ensure diversity, participants were recruited from different faculties and academic majors. All of them had used an AI-assisted argumentation coaching application as part of their daily study routine for at least eight weeks before the data were collected.

The model included three independent variables that captured different dimensions of learner–AI interaction. Data were gathered through a structured questionnaire using a 5-point Likert scale, ranging from 1 (strongly disagree) to 5 (strongly agree).

The first independent variable, Perceived Usefulness of AI Feedback (PUAF), referred to the extent to which learners believed that AI feedback improved their argumentative performance. Drawing on Fred D. Davis (1989), the scale included items related to identifying logical fallacies, improving expected IELTS scores, and refining argument structure.

The second variable, AI-Mediated Argumentative Scaffolding (AMAS), described the extent to which AI support helped learners progress from their current level to more advanced argumentative performance. Based on Kyoo-Lak Cho and David H. Jonassen (2002), the items addressed the provision of clear templates, prompts for supporting evidence, and organizational guidance.

The third variable, Cognitive Engagement with AI (CEAI), assessed learners' self-reported engagement and effort during AI-assisted argumentation practice**.** Conceptually informed by Jennifer A. Fredricks et al. (2004), the three-item measure addressed time spent analyzing AI-proposed counter-arguments, attempts to incorporate advanced vocabulary into subsequent practice, and motivation to deepen spoken arguments. CEAI therefore represents a self-report composite of perceived cognitive engagement rather than an objective measure of processing depth or logged practice duration. Because one item explicitly referred to time spent analyzing counter-arguments, the measure may partly combine perceived time investment with deeper processing; this distinction is taken into account when interpreting the CEAI findings.

The dependent variable, Speaking Self-Efficacy (SSE), reflected learners' confidence in their ability to perform speaking tasks successfully. Following Gülten Genç et al. (2016), the items measured confidence in sustaining extended discussions, using complex sentence structures, and producing coherent arguments.

All quantitative data were analyzed using SPSS. The analysis began with descriptive statistics and bivariate correlations. Internal consistency was assessed through Cronbach's alpha. Exploratory factor analysis, using a pattern matrix, was conducted to examine the factor structure and provide evidence for construct validity. Finally, multiple regression analysis examined the statistical associations of PUAF, AMAS, and CEAI with speaking self-efficacy while accounting for the other variables in the model. Because the quantitative data were cross-sectional, the regression coefficients were interpreted as

conditional associations rather than causal effects. Independent-samples t-tests were also performed to explore possible differences across demographic groups.

### Qualitative Phase: Thematic Analysis and Detailed Transcript Annotation

After completing the quantitative analysis, the study moved to a qualitative phase to better understand the cognitive and affective factors behind the statistical patterns. Eight participants were purposively selected from the original quantitative cohort to provide variation in gender, year of study, and IELTS target. The follow-up interviews were then used to illuminate the contrasting quantitative patterns, particularly the significant PUAF–SSE and AMAS–SSE associations and the non-significant CEAI–SSE association. The resulting sample comprised four female and four male learners and represented all four years of study, and covered IELTS target scores from 6.5 to 8.0. The eight participants, labeled P1 to P8, participated in in-depth, semi-structured interviews.

The interviews were audio-recorded and transcribed using selected transcription conventions presented by J. Maxwell Atkinson and John Heritage (1984). The displayed excerpts retained only limited pause information for transcriptional transparency: (.) indicates a brief micro-pause, while numbers in parentheses (e.g., 0.5) indicate pause duration in seconds. Arrow markers, latching notation, and parenthetical analytic labels were removed from the revised excerpts because they were not required for the thematic analysis. These delivery features were not treated as direct indicators of participants' underlying cognitive or emotional states.

The primary qualitative analytic method was thematic analysis, following Virginia Braun and Victoria Clarke (2006). The analysis involved identifying recurring patterns across the interview data, organizing them into broader themes, and refining related subthemes to examine how participants described AI-assisted scaffolding, psychological safety, cognitive limits, and speaking confidence.

## QUANTITATIVE RESULTS

The quantitative analysis examines the statistical relationships between the measured dimensions of learner–AI interaction and speaking self-efficacy. The sample consisted of 130 valid responses. The results are presented systematically across six discrete analytical tables.

### Demographic Profiles and Measurement Reliability

Table 1 details the demographic composition of the quantitative sample (N = 130), segmented by gender and academic year. The gender distribution was relatively balanced, with 62 male participants (47.7%) and 68 female participants (52.3%). Participants were also represented across all four years of study.

**Table 1.** Participant Demographics (N = 130)

| Demographic Variable | Category | Frequency | Percentage (%) |
|---|---|---|---|
| **Gender** | Male | 62 | 47.7 |
| | Female | 68 | 52.3 |
| **Year of Study** | Year 1 | 28 | 21.5 |
| | Year 2 | 30 | 23.1 |
| | Year 3 | 33 | 25.4 |
| | Year 4 | 39 | 30.0 |

To ensure the psychometric soundness of the survey instrument, reliability analysis was conducted. As presented in Table 2, all constructs yielded Cronbach's Alpha coefficients exceeding the rigorous academic threshold of .80 (ranging from .813 to .840), indicating excellent internal consistency for the adapted measurement scales.

**Table 2.** Reliability Analysis Results

| Construct | Number of Items | Cronbach's Alpha ($\alpha$) |
|---|---|---|
| **Perceived Usefulness of AI Feedback (PUAF)** | 3 | .821 |
| **AI-Mediated Argumentative Scaffolding (AMAS)** | 3 | .824 |
| **Cognitive Engagement with AI (CEAI)** | 3 | .813 |
| **Speaking Self-Efficacy (SSE)** | 3 | .840 |

### Construct Validity and Correlational Analysis

An Exploratory Factor Analysis utilizing Principal Axis Factoring with Promax rotation was conducted. The Kaiser-Meyer-Olkin measure indicated adequate sampling ($KMO$ = .781), and Bartlett's Test of Sphericity was highly significant ($p < .001$).

The Pattern Matrix (Table 3) confirmed that the 12 survey items loaded cleanly onto their four respective theoretical factors without significant cross-loading. Factor loadings ranged from .715 to .891, supporting the intended four-factor structure of the self-report instrument**.** This evidence concerns the internal structure of the questionnaire and does not establish correspondence between CEAI scores and objectively observed cognitive processing.

**Table 3.** Pattern Matrix for Exploratory Factor Analysis

| Items | Factor 1 (SSE) | Factor 2 (AMAS) | Factor 3 (PUAF) | Factor 4 (CEAI) |
|---|---|---|---|---|
| **SSE_1** | .891 | | | |
| **SSE_2** | .766 | | | |
| **SSE_3** | .715 | | | |
| **AMAS_3** | | .824 | | |
| **AMAS_2** | | .805 | | |
| **AMAS_1** | | .715 | | |
| **PUAF_2** | | | .805 | |
| **PUAF_3** | | | .762 | |
| **PUAF_1** | | | .741 | |
| **CEAI_3** | | | | .813 |
| **CEAI_1** | | | | .763 |
| **CEAI_2** | | | | .717 |

*Note: Loadings below .30 are suppressed for clarity.*

Table 4 presents the descriptive statistics and bivariate correlations. Perceived Usefulness of AI Feedback exhibited the strongest positive correlation with Speaking Self-Efficacy ($r$ = .456, $p$ < .001), followed closely by AI-Mediated Argumentative Scaffolding ($r$ = .340, $p$ < .001). Notably, the correlation between Cognitive Engagement with AI and Speaking Self-Efficacy was extremely weak and not statistically significant ($r$ = .076, $p$ = .391).

**Table 4.** Descriptive Statistics and Bivariate Correlations

| Variables | Mean | SD | 1 (PUAF) | 2 (AMAS) | 3 (CEAI) | 4 (SSE) |
|---|---|---|---|---|---|---|
| **1. PUAF** | 3.39 | 0.81 | 1 | | | |
| **2. AMAS** | 3.42 | 0.80 | .220* | 1 | | |
| **3. CEAI** | 3.38 | 0.83 | .292** | -.062 | 1 | |
| **4. SSE** | 3.48 | 0.82 | .456** | .340** | .076 | 1 |

*Note: ** $p$ < .01, * $p$ < .05.*

## Regression Modeling and Demographic Comparison

A multiple regression analysis was conducted to examine the adjusted associations of PUAF, AMAS, and CEAI with Speaking Self-Efficacy. The overall model was statistically significant, $F$ = 15.434, $p$ < .001, and accounted for 26.9% of the variance in self-efficacy ($R^2$ = .269). Collinearity diagnostics showed no evidence of multicollinearity, with variance inflation factors ranging from 1.070 to 1.165.

As presented in Table 5, Perceived Usefulness of AI Feedback showed the largest positive association with Speaking Self-Efficacy in the regression model ($\beta$ = .410, $p$ < .001). AI-Mediated Argumentative Scaffolding was also positively associated with Speaking Self-Efficacy after accounting for the other predictors ($\beta$ = .248, $p$ = .002). In contrast, Cognitive Engagement with AI was not significantly associated with self-efficacy in the adjusted model ($\beta$ = −.028, $p$ = .725), consistent with the earlier correlational findings. Because CEAI was a self-report composite that included both perceived effort and an item referring to time spent analyzing counter-arguments, this result should be interpreted specifically as a non-significant association for the measured CEAI construct. It does not establish that objectively observed processing depth or actual practice duration is unrelated to speaking self-efficacy.

**Table 5.** Multiple Regression Analysis Results (Dependent Variable: SSE)

| **Predictor Variables** | ***Unstandardized B*** | ***Std. Error*** | ***Standardized Beta (β)*** | ***t-value*** | ***p-value*** | ***VIF*** |
|---|---|---|---|---|---|---|
| **(Constant)** | 1.298 | .407 | | 3.187 | .002 | |
| **PUAF** | .415 | .083 | .410 | 4.980 | <.001 | 1.165 |
| **AMAS** | .254 | .081 | .248 | 3.146 | .002 | 1.070 |
| **CEAI** | -.028 | .079 | -.028 | -0.353 | .725 | 1.113 |

*Note: Model R-squared* = .269, *Adjusted R-squared* = .251, $F$ = 15.434, $p$ < .001.

Finally, an independent-samples t-test was conducted to investigate potential gender differences in reported Speaking Self-Efficacy. Levene's Test indicated that equal variances could not be assumed ($F$ = 14.156, $p$ < .001); therefore, the unequal-variances estimate with adjusted degrees of freedom was used. Female participants reported a higher sample mean ($M$ = 3.59, $SD$ = 0.67) than male participants ($M$ = 3.36, $SD$ = 0.94), but the difference was not statistically significant in this sample, $t$ = −1.636, $df$ = 115.95, $p$ = .105. The result should not be interpreted as demonstrating gender equivalence or a universal gender-independent effect of AI-assisted practice.

**Table 6.** Independent-Samples t-Test for Gender Differences in SSE

| Gender | *N* | *Mean* | *SD* | *t-value* | *df* | *p-value* |
|---|---|---|---|---|---|---|
| **Male** | 62 | 3.36 | 0.94 | -1.636 | 115.95 | .105 |
| **Female** | 68 | 3.59 | 0.67 | | | |

*Note: Equal variances were not assumed because Levene's test was significant (p < .001); the reported t statistic and degrees of freedom therefore correspond to the unequal-variances estimate.*

## DISCUSSION: SYNTHESIZING QUANTITATIVE AND QUALITATIVE EVIDENCE

Integrating the regression results with the thematic analysis of the interview data offers a more nuanced picture of the relationships between learners' reported experiences with AI and speaking self-efficacy. In particular, the qualitative data provide contextual insight into the contrasting quantitative findings, including the non-significant association between CEAI and SSE.

The qualitative phase was designed for explanation rather than statistical generalization. The eight follow-up participants represented variation in gender, year of study, IELTS target, and experiences relevant to the principal quantitative findings. In particular, the sample included accounts related to AI-mediated scaffolding, perceived usefulness and psychological safety, and the unexpected non-significant CEAI–SSE association. The interview transcripts were analyzed thematically, while selected timing and delivery features were retained in the displayed excerpts to preserve aspects of how participants expressed their accounts. These transcriptional details were treated as contextual features of recorded speech rather than as independent evidence of cognitive processes. The characteristics of the interview participants are presented in Table 7. Table 8 explicitly connects the principal quantitative findings with the qualitative themes used to interpret them, while Figure 1 illustrates the distribution and density of qualitative codes.

**Table 7.** Profiles of Purposively Selected Interview Participants (N = 8)

| ID | Gender | Year | IELTS Target | Key Observation from Transcript |
|---|---|---|---|---|
| **P1** | Female | 3 | 7.5 | Focused on PEEL structure and complexity. |
| **P2** | Male | 2 | 7.0 | Highlighted logical precision and remaining "fear of humans". |
| **P3** | Female | 4 | 8.0 | Experienced boredom and repetition calling the CEAI finding into question. |
| **P4** | Male | 1 | 6.5 | Improved answer length through connectives. |
| **P5** | Female | 3 | 7.0 | Valued psychological safety and possibility to practice in informal home setting. |
| **P6** | Male | 4 | 7.5 | Noted diminishing returns of long practice sessions. |

| | | | | |
|---|---|---|---|---|
| **P7** | Female | 2 | 6.5 | Relied on AI for "logical paths" to avoid getting lost. |
| **P8** | Male | 3 | 7.0 | Used AI as a mirror to fix conclusion-evidence links. |

*Note. Participants were selected from the quantitative cohort to provide variation in gender, year of study, and IELTS target. The follow-up interviews were used to illuminate the principal quantitative patterns. Participants were not classified as regression outliers or formal extreme-score cases.*

**Table 8.** Integration of Quantitative Findings and Qualitative Explanatory Themes

| Quantitative finding addressed | Qualitative theme | Sub-theme | Participants | Refs | Selected Quotes (Evidence) |
|---|---|---|---|---|---|
| **AMAS–SSE: β = .248, p = .002** | Structural Scaffolding | Logical Templates | P1, P2, P3, P4, P7, P8 | 6 | "It gives me the 'skeleton'... without the AI, my ideas are just messy." (P1) |
| **AMAS–SSE: β = .248, p = .002** | Structural Scaffolding | Complexity & Connectives | P2, P4, P5, P7 | 4 | "It showed me how to use 'consequently'." (P4) |
| **PUAF–SSE: β = .410, p < .001** | Psychological Safety | Non-judgmental Space | P1, P2, P3, P4, P5, P8 | 6 | "I can fail... and it doesn't judge me." (P2) |
| **PUAF–SSE: β = .410, p < .001** | Psychological Safety | Human-AI Gap | P2, P6, P7 | 3 | "A human examiner has facial expressions... AI doesn't have that pressure." (P2) |
| **CEAI–SSE: β = −.028, p = .725** | Cognitive Limits | Diminishing Returns | P3, P6 | 2 | "When I use it for two hours... the feedback starts to look the same." (P6) |
| **CEAI–SSE: β = −.028, p = .725** | Cognitive Limits | Resource Dependency | P2, P5, P8 | 3 | "If I don't read the news, even the AI can't help me with ideas." (P2) |

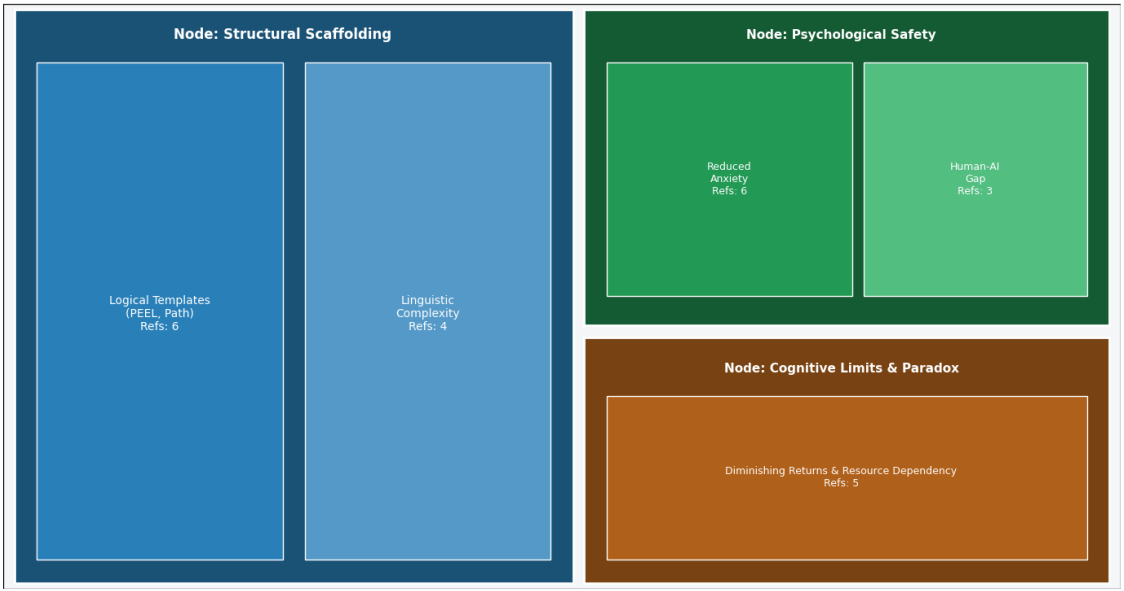


**Figure 1.** Hierarchy chart representing coding density from semi-structured interviews. The area of each node corresponds to the frequency of references, highlighting Structural Scaffolding as the primary perceived benefit of AI-assisted argumentation.

### Theme 1: Structural Scaffolding and the Architecture of Argumentation

The positive association between AI-Mediated Argumentative Scaffolding (AMAS) and Speaking Self-Efficacy ($\beta$ = .248) converged with interview accounts emphasizing structural support. Several participants described difficulty organizing ideas under real-time pressure and reported templates or guiding prompts as useful for structuring their responses. The qualitative findings therefore contextualize the AMAS–SSE association without establishing that AI scaffolding caused greater confidence or argumentative performance.

In these accounts, AI was perceived as an external organizational aid that provided templates and prompts for structuring arguments. Rather than establishing that AI itself produced more coherent or confident speech, the evidence indicates that participants perceived this structural support as useful.

Participant 1's account illustrates how one learner described using a logical template during AI-assisted practice. The detailed transcript preserves pauses and other features of delivery, while the interpretation rests primarily on the content of the participant's account rather than on inferring cognitive states from transcription symbols.

**Excerpt 5.1.** P1: Structural Scaffolding

1 IN: can you (.) describe a specific instance where
2 the AI coach challenged your argument?
3 P1: well (0.4) um (.) it was last week (.) I think.
4 (0.2) we were practicing (0.5) uh (.) a topic
5 about fast food in schools. (0.3) I said (0.2)

you know (.) it's bad for kids' health.
(0.4) but then (.) the AI coach (.) it asked
me (0.2) what about the freedom of choice for
students? (0.5) I was (0.3) um (.) quite
surprised. I mean (.) I never thought about it
from that side.
(0.4) so (.) it forced me to use the PEEL
structure (.) you know (.) point (.) evidence (.)
and then a counter-argument.
(0.5) it changed how I think about (0.3) uh (.)
the complexity of an answer.

The transcript preserves several timed pauses as P1 recalls the experience. These pauses are reported as features of delivery and are not interpreted as direct measures of cognitive load. More substantively, P1 explicitly described using the PEEL structure after being prompted to consider a counter-argument, providing qualitative evidence of the learner's perceived use of structural scaffolding.

Participant 4 similarly described syntactic scaffolding in relation to perceived argumentative depth:

**Excerpt 5.2.** P4: Syntactic Complexity

P4: um (0.3) let me see. (0.4) ah (.) the topic was
about (0.2) uh (.) social media. (0.3) I used to
just say I like it. (0.2) but the AI (.) it
pushed me to (.) um (.) give a reason and a result.
(0.4) it showed me how to use consequently (.)
you know? (0.3) it made my short answers (.) um
(.) longer and more (.) uh (.) academic.

P4's account suggests that prompts to use specific connectives were perceived as helping expand a brief response into more elaborated cause-and-effect argumentation. Participant 7 similarly described the AI as providing a "clear path" when organizing ideas.

### Theme 2: Psychological Safety and the Non-Judgmental Buffer

A recurrent qualitative theme was reduced social-evaluation anxiety during AI-assisted practice. This theme provides contextual support for interpreting the positive association between Perceived Usefulness of AI Feedback and Speaking Self-Efficacy (PUAF, $\beta$ = .410). Participants frequently described the absence of immediate human evaluation as making AI-assisted practice feel less judgmental.

Participants commonly described AI-assisted practice as less socially evaluative than interaction with a human interlocutor, which they associated with reduced anxiety during practice. Participant 2 elaborates on this contrast:

**Excerpt 5.3.** P2: Psychological Safety

IN: how has the non-judgmental nature of AI impacted
your confidence?
P2: oh (.) this is the best part! With a teacher I'm
always (.) uh (.) scared of making grammar mistakes.
(0.3) but with the AI (.) it's just a screen (.)
you know? (0.4) I can fail (.) I can (.) um (.)
stutter (.) and it doesn't judge me.
(0.5) it taught me to be more (.) um (.) precise (.)
I mean (.) more careful with always or never. (0.4)
that makes me feel (.) well (.) brave enough to try
longer sentences.

P2's account directly contrasts the anxiety associated with teacher interaction with the perceived non-judgmental nature of AI-assisted practice. The thematic interpretation therefore rests on the participant's explicit description of being afraid of making mistakes with a teacher and feeling able to fail or stutter without judgment when practicing with AI. This account contributes to the theme of psychological safety. Participant 5 echoes this sense of psychological comfort:

**Excerpt 5.4.** P5: Environmental Safety

P5: yes (.) because it's (.) uh (.) anonymous.
(0.3) I can practice in my (.) um (.) pajamas and
nobody cares. (0.4) it's very (.) well (.) relaxing.

However, participants' accounts also suggest a possible gap between confidence during AI-assisted practice and confidence with a human interlocutor. P2, for example, reported feeling more confident with AI while remaining nervous about a human examiner:

**Excerpt 5.5.** P2: The Human-AI Gap

P2: but (.) to be honest (.) I'm still a bit (.) uh (.)
nervous about a real human.
(0.4) a human examiner has eyes (.) they (.) they
look at you.
(0.3) AI doesn't have that pressure (.) so I feel
brave with AI (.) but maybe still (.) um (.)
scared of humans.

This account raises the possibility of a transfer gap between AI-assisted practice and practice with a human interlocutor. Maintaining opportunities for human interaction during exam preparation may therefore be pedagogically useful, although the present study cannot determine an optimal sequence or establish that such practice causes better transfer.

### Theme 3: Cognitive Engagement and a Proposed Threshold Interpretation

A theoretically important finding was the non-significant adjusted association between Cognitive Engagement with AI (CEAI) and Speaking Self-Efficacy ($\beta = -.028$, $p = .725$). Within this sample, higher self-reported CEAI did not correspond to higher SSE after PUAF and AMAS were taken into account. This contrasts with the positive associations observed for perceived usefulness and argumentative scaffolding and indicates that these dimensions of AI-assisted practice should not be treated as interchangeable. CEAI was a self-report composite, and one item referred explicitly to perceived time spent analyzing counter-arguments; therefore, the result cannot disentangle actual practice duration from depth of cognitive processing.

The thematic analysis offers possible contextual interpretations of this statistical pattern, including reports of repetition, fatigue, and reliance on AI-generated structures. These interview accounts remain perceptual evidence and cannot independently verify participants' cognitive-processing depth. Participant 3, a Year 4 learner with an IELTS target of 8.0 whose account was particularly relevant to the CEAI finding, described repetition and feedback fatigue during extended AI practice:

**Excerpt 5.6.** P3: Repetition and Feedback Fatigue

P3: actually (0.5) um (.) this is a bit hard to say.
(0.3) I spent (.) like (.) two hours every day.
(0.6) but (.) uh (.) after a while (.) it felt a
bit repetitive. (0.4) it kept saying the same
feedback (.) like (.) add more examples.
(0.3) even when I thought my example was good.
(0.5) so (.) um (.) I spend time on it (.) but I
don't feel my confidence is (.) you know (.) growing
more. (0.4) it's a bit (.) uh (.) boring sometimes.
(0.3) sometimes I feel I'm just (.) you know (.)
following a machine. (0.4) I'm not sure if my depth
is real or just (.) uh (.) a template.

The transcript preserves several pauses as P3 describes extended practice. Rather than treating these pauses as evidence of cognitive strain, the analysis focuses on P3's explicit reports of repetition, boredom, and uncertainty about whether the perceived argumentative depth was internally generated or template-driven. Participant 6 described a related experience of fatigue during longer practice sessions:

**Excerpt 5.7.** P6: Practice Fatigue and Perceived Diminishing Returns

P6: honestly (.) I think (0.2) uh (.) using it for
thirty minutes is enough.
(0.4) when I use it for two hours (.) I feel (.) um
(.) my brain is tired and the feedback starts to
(.) uh (.) look the same.
(0.5) I don't think more time means more confidence.

P6's account is consistent with a possible cognitive-threshold interpretation but does not validate the existence of a statistical threshold. Together with other reports of repetition and dependency, it offers one possible interpretation of the non-significant association between CEAI and SSE. Because the quantitative design did not separately measure logged practice duration or objectively observed processing depth, alternative explanations for this pattern remain possible.

**Excerpt 5.8.** P8 & P2: Resource Dependency

P8: it helps me (.) uh (.) see the other side of the coin. (0.4) but I think (.) um (.) my reading habits also matter a lot. (0.3) AI is just a (.) uh (.) mirror for my thoughts.
P2: honestly (.) if I don't read the news (.) even the AI can't help me with ideas. (0.4) so it's (.) um (.) fifty-fifty.

These accounts suggest that participants viewed AI more as an organizational aid than as a substitute for substantive knowledge. P8 and P2 emphasized the continuing importance of reading and independent knowledge development. Their comments raise the possibility that extensive reliance on AI-generated structures may be accompanied by perceived dependency or cognitive offloading; however, the present study cannot establish whether such reliance causes speaking self-efficacy to plateau or decline.

The contribution of the study is therefore threefold. First, it examines AI-assisted speaking in the specific context of spontaneous IELTS Part 3 argumentation, where learners must organize, support, and qualify ideas in real time. Second, it distinguishes perceived usefulness, argumentative scaffolding, and self-reported cognitive engagement rather than treating AI use as a single construct. Third, the integration of the non-significant CEAI finding with participants' accounts generates a provisional cognitive-threshold hypothesis that can be tested directly in future longitudinal or experimental research.

## LIMITATIONS AND FUTURE RESEARCH

Although this study offers useful insights into AI-assisted speaking practice, several limitations should be acknowledged. First, the quantitative phase relied on self-reporting questionnaires, which may be affected by social desirability, recall bias, and differences in how accurately learners assess their own engagement. This issue is particularly relevant to CEAI. The CEAI measure combined self-reported indicators of cognitive effort with one item referring to perceived time spent analyzing counter-arguments, while no interaction-log data or independent behavioral measures were available to distinguish actual practice duration from processing depth. Consequently, the non-significant CEAI–SSE association should not be interpreted as evidence that deeper cognitive processing itself is unrelated to speaking self-efficacy.

Second, the qualitative phase involved eight purposively selected follow-up participants from a single higher education institution in Vietnam. Selection was designed to capture variation in gender, year of study, and IELTS target. The interviews were subsequently used to explore experiences relevant to the quantitative findings, but the qualitative phase was intended for explanation rather than statistical representation. The single-institution context further limits transferability to other educational and cultural settings.

Third, the quantitative phase used a cross-sectional design in which the study variables were measured at a single time point after participants had already used the AI-assisted application for at least eight weeks. No pre-use baseline measure of speaking self-efficacy or non-AI comparison group was included. Consequently, temporal ordering and causal effects cannot be established, and the regression coefficients should be interpreted as associations within this sample rather than evidence that AI coaching caused changes in speaking self-efficacy.

The gender comparison should also be interpreted cautiously. No statistically significant gender difference in SSE was detected in this sample, but the study was not designed as an equivalence test; therefore, the result does not establish that male and female learners respond identically to AI-assisted practice.

Another limitation concerns the possible novelty effect and the changing nature of commercial AI systems. Learners' initial enthusiasm may affect perceptions of usefulness or engagement, while system updates may make exact replication of AI-assisted practice conditions difficult.

Future research should therefore use longitudinal pre- and post-test designs and, where feasible, experimental or quasi-experimental comparisons. It should also triangulate self-reported cognitive engagement with behavioral evidence from AI interactions, such as response length, requests for clarification or challenge, revision cycles, and uptake or modification of AI-suggested argumentative structures. These traces could be combined with independent coding of response quality or argumentative development to distinguish time spent interacting with AI from deeper processing. Behavioral traces should be treated as complementary indicators rather than direct substitutes for cognitive states. Future studies should additionally include objective, rater-based speaking assessments and more diverse learner populations.

## CONCLUSION AND PEDAGOGICAL IMPLICATIONS

This study offers empirical insight into the relationships among learners' perceptions of AI-assisted argumentation coaching, cognitive engagement, and speaking self-efficacy in a high-stakes language-learning context. By adopting an explanatory sequential mixed-methods design, the study connected cross-sectional statistical patterns with learners' accounts of AI-assisted speaking practice.

Perceived Usefulness of AI Feedback and AI-Mediated Argumentative Scaffolding were positively associated with Speaking Self-Efficacy, whereas self-reported Cognitive Engagement with AI was not significantly associated with SSE after accounting for the other predictors. The interview accounts complemented these statistical patterns:

participants frequently described structural guidance and a nonjudgmental practice environment as helpful for confidence, while some also reported repetition, fatigue, or dependence during prolonged AI use. These accounts help interpret the observed associations but do not establish causal pathways.

The principal theoretical contribution of the study is a provisional cognitive-threshold hypothesis for AI-mediated engagement in spontaneous argumentative speaking. The contrasting quantitative pattern, together with participants' reports of repetition, fatigue, and dependency, suggests that the perceived benefits of AI-assisted practice may depend on how learners use and respond to the support rather than on greater reported cognitive engagement alone. However, the present study does not demonstrate a nonlinear trajectory, identify a threshold point, or establish a causal mechanism. The proposed threshold should therefore be understood as a testable conceptual hypothesis generated by the integrated mixed-methods findings.

More broadly, the study contributes to AI-assisted language-learning research by shifting attention from whether AI improves speaking to how different dimensions of AI-assisted support are related to confidence during cognitively demanding, spontaneous argumentation.

The findings also suggest several pedagogical considerations. Educators may guide students toward focused and purposeful AI use while maintaining opportunities for independent reasoning and human-to-human interaction. Participants' reports of repetition, fatigue, and dependency suggest that prolonged reliance deserves attention, although the present study cannot determine whether particular practice durations cause these outcomes. These recommendations should therefore be understood as pedagogical implications arising from the observed associations and qualitative accounts rather than evidence of intervention effectiveness**.**

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