Using Copilot to Foster Utterance Fluency of Undergraduates: A Multiple Case Study

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ABSTRACT

Utterance fluency in a second language (L2) is essential for communicative competence, yet many learners face psychological barriers such as speaking anxiety and fear of social judgment. In EFL contexts like Vietnam, where English learning is primarily classroom-based, opportunities for authentic oral interaction are limited. This study explores the potential of Copilot voice mode, an AI-driven conversational tool, to support speaking fluency development and reduce psychological barriers. Using a multiple case study design, three Vietnamese university students, at Beginner, Pre-Intermediate, and Intermediate proficiency levels, participated in an eight-week intervention. Data sources included pre- and post-tests analyzed using ELSA Speech Analyzer, participant audio recordings, and self-reflections coded thematically. Results suggest that Copilot may facilitate improvements in utterance fluency and learner confidence, particularly for lower-proficiency learners. While limitations in AI accuracy and voice recognition were noted, the tool offered accessible, low-pressure speaking opportunities. This study highlights the value of integrating AI tools like Copilot into language education and offers practical insights for supporting speaking development in resource-constrained EFL contexts.

Keywords: speaking fluency, AI-driven learning, Copilot voice mode, fluency development, EFL learners

Introduction

Speaking fluency is essential for effective communication in a second language (L2), particularly in English as a Foreign Language (EFL) contexts like Vietnam, where learners have limited access to authentic interaction. Fluency enhances learners' global communication skills, employability, and confidence in both professional and social settings (Nguyen, 2017). In this study, utterance fluency refers to the smoothness and flow of spoken language, specifically speech rate, pauses, and articulation, which reflect the ability to speak in real time (Tavakoli, 2025).

Despite its importance, English instruction in Vietnam has traditionally emphasized grammar and reading over oral communication (Denham, 1992), leaving learners underprepared for real-world speaking tasks. Psychological barriers such as anxiety, fear of errors, and reluctance to

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speak further inhibit fluency development (Le & Nguyen, 2019). These issues are compounded by the lack of interactive and meaningful speaking opportunities, both in and outside the classroom.

Although conversational AI tools like Elsa Speak and Mondly have shown promise in enhancing L2 fluency, their cost often limits accessibility, especially in public education settings. In contrast, Copilot, a free, AI-driven voice tool, offers a potentially practical and scalable alternative. Despite growing interest in AI applications in education, their integration into Vietnamese EFL classrooms remains limited. Learners still struggle to find engaging, low-pressure environments to practice speaking. To cope with barriers such as cost, foreign language anxiety, and limited exposure, Copilot may be an ideal option, as it will provide learners with a low-pressure, interactive environment to practice speaking without a financial burden. Copilot may help bridge this gap by providing accessible and interactive speaking practice at no cost. However, little empirical research exists on its effectiveness in supporting utterance fluency or reducing language anxiety in the Vietnamese context.

This study aims to address two key gaps in the literature. First, it investigates how Copilot use influences learners' oral utterance fluency. Second, it explores how students perceive the experience of practicing speaking with Copilot, particularly in terms of perceived benefits and challenges.

Literature review

L2 Speaking Fluency and Utterance Fluency

Fluency is a core dimension of L2 oral performance, especially in task-based interaction. Skehan (2003) proposed a widely adopted model of utterance fluency that includes speed (how quickly one speaks), breakdown (frequency and length of pauses), and repair (self-corrections, repetitions). These elements were empirically validated by Tavakoli and Skehan (2005), who treated them as distinct yet related indicators of spoken proficiency. Segalowitz (2010) later expanded the view by distinguishing between cognitive, utterance, and perceived fluency. Of these, utterance fluency refers to measurable aspects of speech, like rate and pause patterns, which reflect underlying cognitive processing. Skehan (2014) refined this further by categorizing fluency at the clause, discourse, and overall rate levels, helping to distinguish between planning effort and delivery flow. Tavakoli and Hunter (2018) introduced a continuum, from broad fluency linked to general L2 ability to narrower definitions based on speech timing. This study adopts the narrow view, focusing on quantifiable features and excluding listener-based impressions.

Scholars often judge second language fluency using a few clear signs. These include the speed at which someone talks (speech rate), the number of syllables they can say before pausing (mean length of run), the placement of those pauses within a sentence, and the frequency with which the speaker corrects their own speech (repair strategies) (Skehan, 2003; Tavakoli & Skehan, 2005). Fathi et al. (2024) looked at how groups of words that often appear together, known as lexical bundles, shape how fluent a speaker sounds to others. Taking these ideas further, this study looks at specific features within spoken sentences: pausing patterns, delivery speed, and instances of self-correction, which give a clearer picture of how someone's fluency is improving.

AI-Based Speech Evaluation in L2 Fluency Assessment

Today, AI-based tools like Automatic Speech Evaluation (ASE) make it easier to assess spoken fluency. They turn speech into text, identify features like speech rate, pauses, pronunciation, and repairs, and then assign a score (Handley & Wang, 2018). These scores are based on human-rated examples and match well with fluency research (Zechner et al., 2009; Wang et al., 2018; Chen et al., 2018; Segalowitz, 2010; Tavakoli & Hunter, 2018). ASE tools are now widely used to give useful feedback to both learners and teachers.

A variety of ASE programs are currently accessible to facilitate automated evaluation and learner feedback. For example, Duolingo English Test, ETS's SpeechRater, and Pearson's Versant system have all incorporated AI-based fluency scoring in high-stakes testing (e.g., Zechner et al., 2009; Bernstein et al., 2010). These tools generally focus on large-scale validation and automated scoring, with limited integration into classroom or learner-directed contexts.

However, as Suzuki & Kormos (2022) note, while technological progress has enhanced the precision of these systems, relatively few studies have examined their pdagogical implications, especially in everyday speaking practice. Most existing work centers on system development or test correlation, leaving a gap in our understanding of how learners interact with these tools and benefit from them in real-time practice settings.

To address this gap, the current study investigates how a commercially available ASE tool, the Elsa Speech Analyzer, can be integrated into L2 speaking practice. Unlike high-stakes testing systems, ELSA is accessible to individual learners and provides detailed, real-time feedback. This study examines both its impact on measurable utterance fluency (e.g., speech rate, pauses, repairs) and learners' perceptions of using AI to support their speaking. This helps show how ASE can be useful in the classroom and gives a clearer view of how it supports students in learning languages through AI.

Copilot: Artificial Intelligence Tool as a Conversational Agent

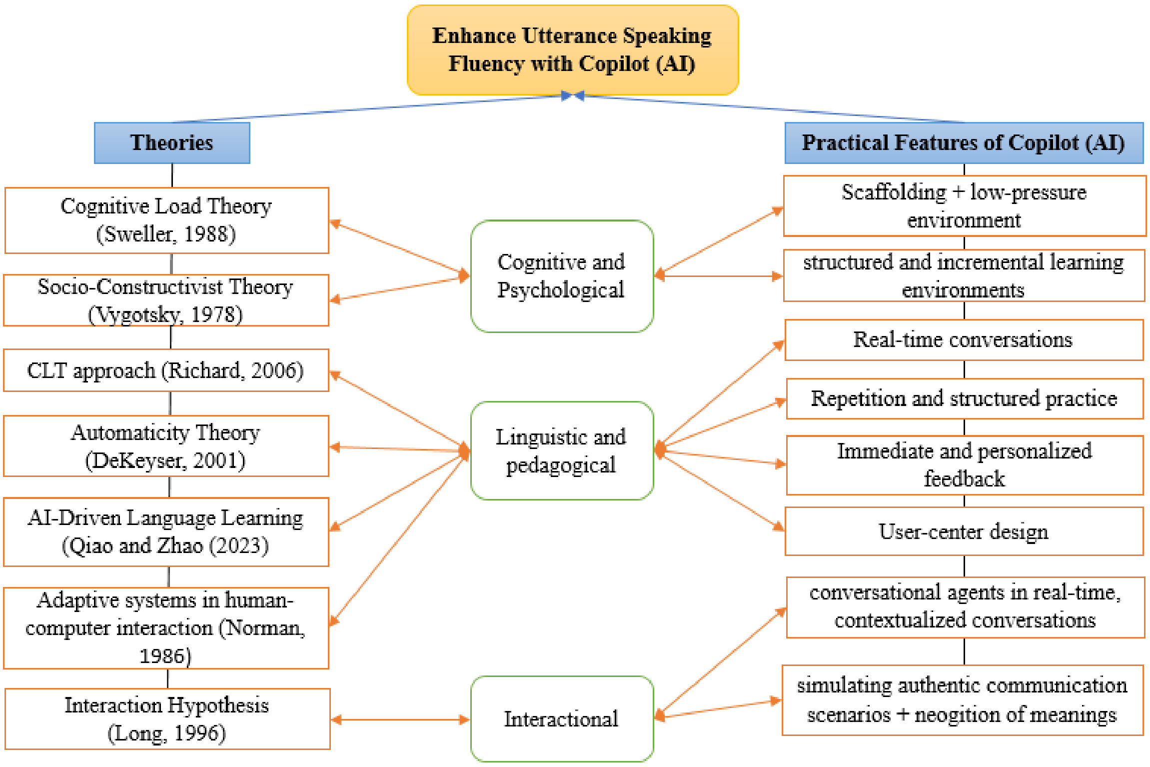
Copilot, developed by Microsoft with OpenAI, has become popular for helping users practice speaking in a low-pressure setting. It offers instant feedback on grammar and vocabulary and adjusts to each learner's level and goals, making speaking practice more personal and less stressful (Brown et al., 2020; Wu & Huang, 2025; Chen, 2024). While it can sometimes misread input or miss cultural meaning (Zhang et al., 2023), Copilot still encourages independent learning and fluency growth, showing the promise of AI in language education.

Theoretical Framework

Building utterance fluency in L2 learners has always been a key part of language education, supported by linguistic, cognitive, and pedagogical theories. Bringing in AI tools like Copilot builds on these ideas to help address fluency difficulties (see Figure 1).

Figure 1.

Theoretical Framework Supporting Copilot AI in Enhancing Utterance Fluency



From a linguistic and pedagogical perspective, Communicative Language Teaching emphasizes real-time interaction and authentic conversation (Richards, 2001), which aligns with Copilot's conversational design. Repetition and practice, emphasized in Automaticity Theory, help learners move from controlled to automatic processing, a process supported by Copilot's structured and adaptive sessions (DeKeyser, 2001). Adaptive systems in human-computer interaction also provide immediate feedback to guide improvement, addressing common fluency barriers such as hesitations and limited vocabulary (Emond, 2021).

Rooted in cognitive psychology, Sweller's (1988) Cognitive Load Theory stresses the need to reduce unnecessary mental load, an aspect directly supported by Copilot's structured, low-pressure learning environment. Copilot supports this by adjusting task difficulty to learners' levels. Similarly, Vygotsky's Socio-Constructivist Theory highlights the importance of expert scaffolding in the Zone of Proximal Development, a role that Copilot can approximate through guided interactions (Vygotsky, 1978). Its low-pressure environment helps reduce anxiety and encourages learners to take risks in speaking.

The Interactionist Theory of SLA and the Interaction Hypothesis stress the role of negotiation of meaning and real-world communication in language acquisition (Long, 1996). Copilot provides authentic, real-time interaction, compensating for limited classroom speaking opportunities. It takes on different speaker roles and gives quick feedback to help learners improve both accuracy and fluency.

Together, these theories suggest that Copilot can help L2 learners build utterance fluency, especially in EFL contexts with limited real-life speaking opportunities. Communicative Language Teaching and the Interaction Hypothesis highlight its value in encouraging meaningful conversation. Automaticity Theory and Cognitive Load Theory show how structured practice improves fluency without overloading the learner. Socio-Constructivist Theory and adaptive human-computer interaction principles support Copilot's ability to guide learners and adjust feedback. While this framework wasn't used to code the data, it still offers a strong base for understanding Copilot's role in teaching. It supports the view that AI tools can help develop speaking fluency when interaction is limited.

Previous Research on Technological Tools to Better English Speaking Skills

Lately, more EFL teachers and learners have started using AI tools to practice speaking. These tools can be helpful, but some problems still exist. They often need strong Internet, do not always fit the classroom, and may not suit all students.

Fathi et al. (2025) looked at how Google Assistant helped learners speak better. Students liked learning alone and getting quick feedback, but the tool did not work well without Internet, and teachers could not guide much in class. In another study, Warman et al. (2023) used AI with quiet university students in Indonesia. It helped reduce stress and made them more willing to speak. Still, the study only focused on introverts, so the results may not apply to all.

Qiao and Zhao (2023) studied Duolingo. It helped students manage their learning and speak more but the app followed a fixed path, so there wasn't much natural conversation. Jeon et al. (2023) looked at SpeakEasy. It gave useful feedback and boosted confidence, but it did not pick up on emotion well and had trouble keeping a real conversation going.

In the Vietnamese EFL context, several studies have explored digital tools for oral skill development. Nguyen and Pham (2022) showed that multimedia tools like YouTube and speech recognition improved students' confidence and motivation. Du et al. (2024) found that digital storytelling through tools like Movie Adventure enhanced fluency and creativity. Duong and Suppasetseree (2024) studied Andy English Bot, a text-based AI chatbot that prevented anxiety and improved accuracy. Despite their contributions, these tools often relied on scripted, text-based, or visual interactions, offering limited opportunities for spontaneous oral fluency development.

While these studies highlight the evolving role of AI in language learning, several limitations persist. Many tools lack real-time oral interaction, level-appropriate scaffolding, or affordability for broad classroom use. Furthermore, few integrate fluency-focused pedagogical principles such as automaticity, interactionist SLA, or cognitive load management.

To address these gaps, this study introduces Copilot AI, a free, voice-enabled tool that provides real-time, adaptive speaking practice. Unlike earlier tools, Copilot supports negotiation of meaning, offers immediate feedback, and adapts to learners' proficiency levels. Its design is grounded in communicative language teaching and second language acquisition theory, making it a promising innovation for enhancing utterance fluency, especially in Vietnamese EFL classrooms where students have limited exposure to authentic English conversation.

Research Gaps

AI is becoming more common in language classrooms, but concerns about cost, learner anxiety, and practical use in EFL settings still need attention. In Vietnam, where access to authentic spoken English is limited, many tools, like Duolingo, SpeakEasy, or VR systems, have shown some benefits (Yang & Wu, 2023; Qiao & Zhao, 2023; Jeon et al., 2023). However, their expense and technical demands often make them unrealistic for regular classroom use. Besides, emotional barriers are also a factor. Students often avoid speaking out of fear, whether it's making mistakes or being judged by peers (Horwitz et al., 1986; MacIntyre & Gardner, 1994). Some researchers suggest that AI may help reduce this pressure (Warman et al., 2023; Wu & Huang, 2025), but few have looked closely at how voice-interactive tools like Copilot might help Vietnamese learners feel more confident. Lastly, real-time speaking practice is rare in EFL classes. Much of the existing work has focused on writing or scripted responses (Du et al., 2024; Duong & Suppasetseree, 2024). The role of Copilot in supporting natural fluency and lowering anxiety remains largely unexplored.

How Copilot Fills the Gaps

Copilot offers a practical and context-responsive solution to the identified challenges. As a free, accessible, and speech-based tool, it removes the cost barrier associated with many other AI solutions. Its real-time feedback and scaffolded conversational design align with cognitive and socio-constructivist learning theories, offering level-appropriate support for learners at various proficiency stages.

Crucially, Copilot also creates a low-stakes environment where learners can speak freely without the fear of social judgment, helping reduce anxiety and encourage risk-taking in oral language use. In Vietnam, where classroom interaction is often limited and spontaneous speech practice is rare, Copilot provides structured yet flexible opportunities for learners to engage in consistent, autonomous practice.

This study addresses the identified research gap by investigating (1) the extent to which Copilot can enhance utterance fluency and (2) learners' perceptions of its role in reducing speaking-related anxiety in an EFL classroom context. In doing so, it offers new insights into the pedagogical potential of conversational AI for inclusive and affordable language learning.

Research Questions

Accordingly, the study is guided by the following research questions:

(1) Does speaking with Copilot improve oral utterance fluency?

(2) What benefits and challenges do students encounter while using Copilot?

Methods

Pedagogical Setting & Participants

This study employed purposeful sampling to select participants aligned with the research objectives (Palinkas et al., 2015). From a cohort of 40 students preparing for the Vietnamese

Standardized Test of English Proficiency (VSTEP), three 20-year-old male learners were selected based on their diagnostic speaking scores. These scores were mapped to CEFR-equivalent proficiency levels, following the VSTEP framework (Ministry of Education and Training, Vietnam): the beginner participant corresponded to A2, the pre-intermediate participant to B1, and the intermediate participant to B1+ approaching B2. This range allowed the study to explore how Copilot supports learners at distinct stages of spoken English development, enabling both within-case depth and cross-case comparison of learning trajectories.

Design of the Study

This study used a multiple-case approach (Yin, 2018) to explore how a conversational AI tool, Copilot, helps EFL learners in Vietnam improve their utterance fluency. This method fit well with the small number of participants and the goal of understanding both personal learning paths and common patterns across cases. The research followed three learners at different English levels: beginner, pre-intermediate, and intermediate, to better understand how students with varied language backgrounds use AI-supported speaking practice.

Data collection & analysis

Following the multiple-case study design (Yin, 2018), this research used two main sources of data across the three cases: (1) performance results from pre- and post-tests analyzed through the ELSA Speech Analyzer, and (2) self-reflection journals written by the learners. These sources made it possible to look closely at each case and also compare across participants.

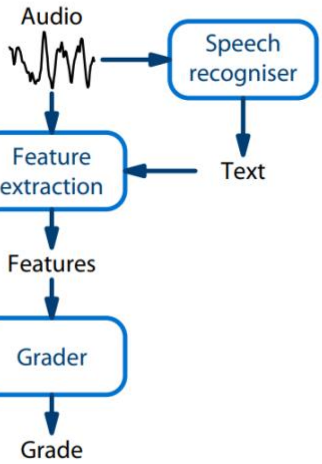
Performance Data via Pre- and Post-Test

To explore whether using Copilot improves utterance fluency, each learner completed a 12-minute speaking test before and after the study. The test followed the official VSTEP speaking exam format, with three parts: Social Interaction (3 minutes), Problem-Solving (4 minutes), and Topic Development (5 minutes). This format ensured consistency with national testing standards and allowed for meaningful comparison.

The recorded responses were processed using the ELSA Speech Analyzer, a tool based on the Automatic Speech Evaluation (ASE) framework (Handley & Wang, 2018). The system transcribed the speech, identified key fluency features such as speech rate, pause duration, and pronunciation accuracy, and then calculated overall fluency scores using models trained on human-rated learner speech (Chen et al., 2018; Zechner et al., 2009).

Figure 2

The Architecture of a Typical Automatic Assessment System for Spoken Language Assessment Was Adopted from Wang et al. (2018, p. 2)



Self-Reflection Journals

To understand learners' experiences with Copilot, each participant submitted weekly self-reflection journals during the 8-week intervention, totaling 24 entries across three cases. These reflections captured emotional engagement, technical issues, and perceived progress, offering rich qualitative data alongside pre–post fluency scores. The journals provided insight into how each learner interacted with the AI tool, interpreted their development, and navigated both benefits and frustrations. This consistent data collection across beginner, pre-intermediate, and intermediate participants enabled both within-case and cross-case analysis, allowing the study to trace individual fluency trajectories while identifying broader patterns in AI-supported language learning.

Data Collection

Phase 1: Getting Started – Week 0

First, a diagnostic speaking test was given to 40 students. The test followed the official VSTEP speaking exam format. Not only did we rely on test scores, but we also considered CEFR levels to make sure the range made sense. Then, each student took a 12-minute pre-test covering three parts: Social Interaction, Problem Solving, and Topic Development. These recordings helped us understand where each student was starting from. After reviewing the scores, three male students were selected, each 20 years old, with clearly different speaking abilities: beginner, pre-intermediate, and intermediate.

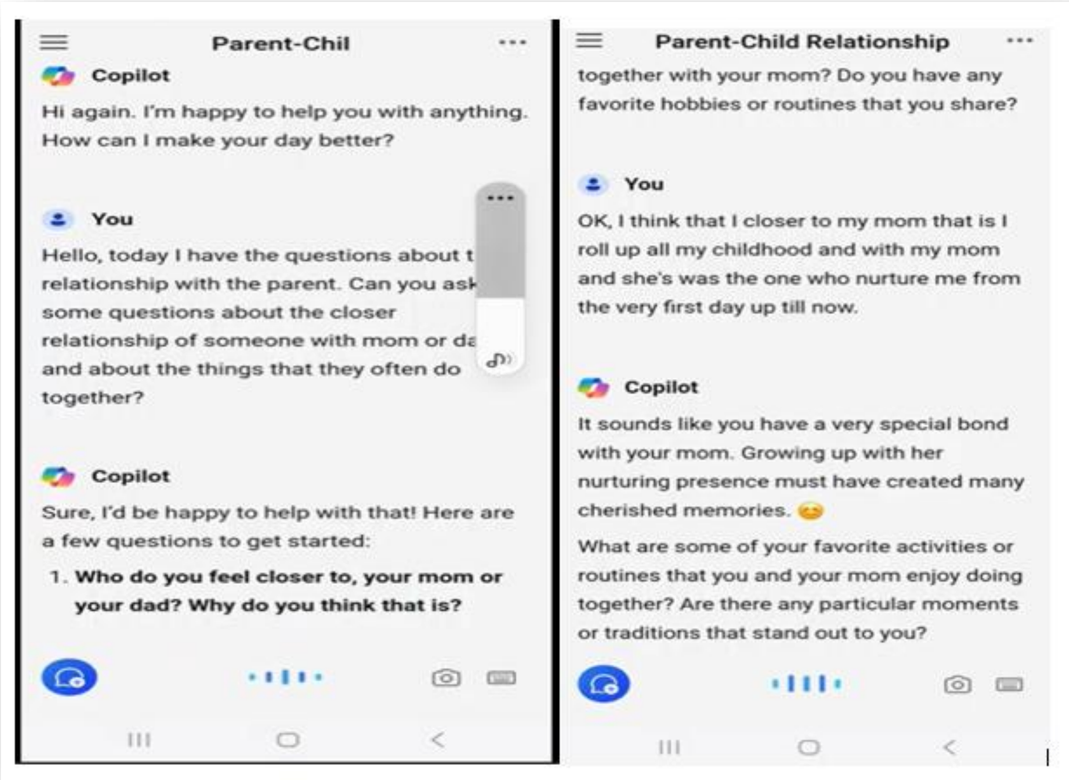
Phase 2: Daily Practice with Copilot – Weeks 1 to 8

After the initial testing, students started daily practice with Copilot. Each day, after learning the speaking topic in class, they spent about 15 minutes talking with the AI, using topics that matched the VSTEP test format. The topics for 8 weeks include bus, gameshows, the place you never want to come back to, book a table at a restaurant, relationship with parents, school discipline, birthdays, and spending money. The idea was to keep things familiar but also useful for real-life speaking.

To begin each session, students typed or said something simple like, “Let’s talk about going to school,” and Copilot responded. From there, the conversation grew naturally. For instance, if the topic was “relationships with parents,” Copilot might ask, “Do you find it easy to talk to your parents?” or “Can you tell me about a disagreement you’ve had?” Students answered, and the AI kept the conversation going by asking follow-up questions. Sometimes, it even offered suggestions to fix their pronunciation or vocabulary. Figure 3 illustrates the conversations between Copilot and participants, screenshots from video recordings.

Figure 3.

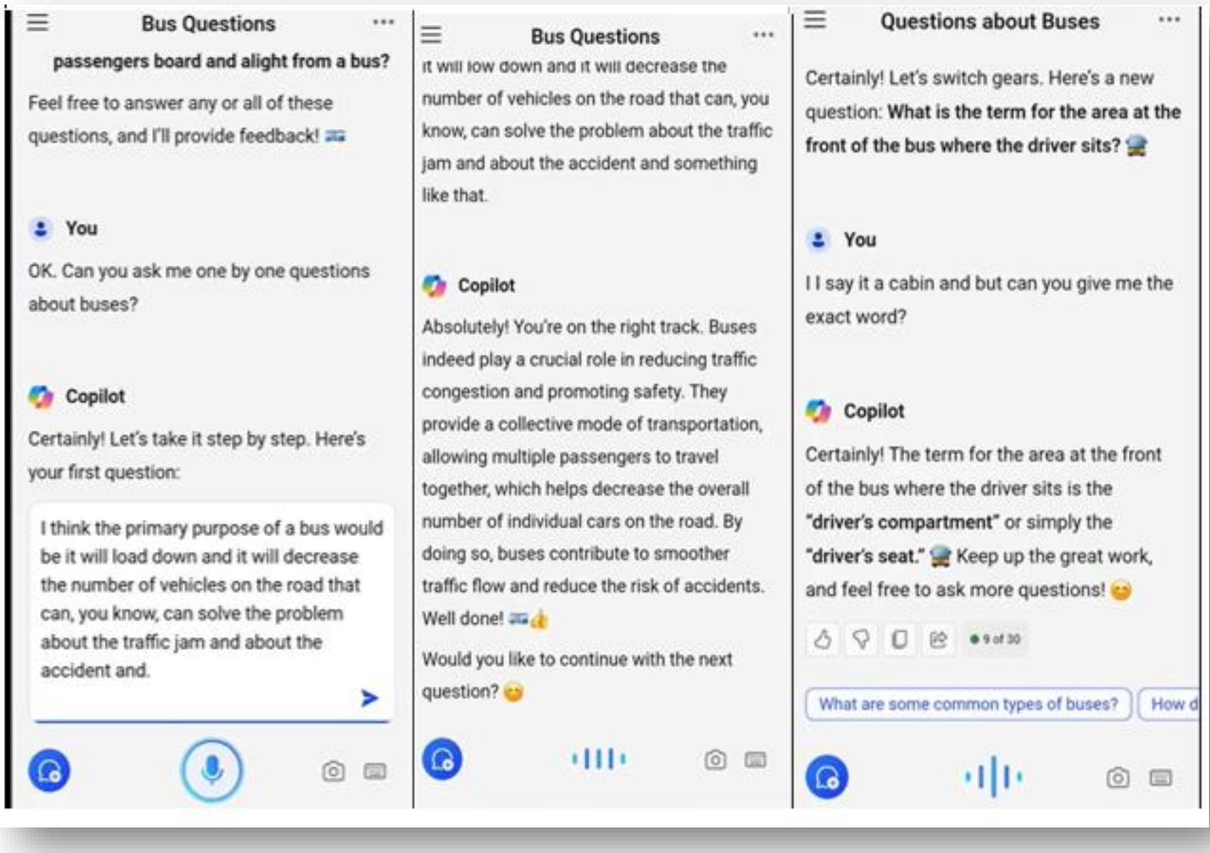
Screenshots from Video Recordings of the Conversation Between Copilot and Participants.



Importantly, students did not just speak; they also got feedback in real time. If someone mispronounced a word or used the wrong verb tense, Copilot would point it out. It was not always perfect, but it helped them notice their mistakes and try again. The participants repeated their sentences to improve. Otherwise, they just moved on and used the feedback the next day. Copilot can perfect the original ideas and provided more relevant information. Figure 4 displays how Copilot gave feedback to participants.

Figure 4.

Copilot's feedback on participants' answers.



At the end of each day, each student wrote a short journal entry. They did not have to be formal, just honest notes about what they learned, what felt difficult, and how they reacted to the AI's feedback. Over 8 weeks, eight reflections were collected from each student, totaling 24 across all three cases.

Phase 3: Post-Test – Week 9

After the 8-week intervention, participants completed a post-test identical in format to the pre-test, following the official VSTEP speaking structure. Recordings were analyzed using the ELSA Speech Analyzer, which provided a composite fluency score along with pacing, pausing, and hesitation metrics. These scores allowed for direct comparison of fluency development. Learners' weekly reflections were also reviewed, enabling a triangulated analysis of both performance outcomes and their experiences using Copilot.

Data Analysis

This study adopted a multiple-case study design (Yin, 2018), treating each participant as an individual unit of analysis. The analytic process followed two major phases: (1) within-case analysis to examine each learner's development across both quantitative and qualitative dimensions; and (2) cross-case synthesis to identify converging patterns and proficiency-specific variations across the three cases. Each case combined two forms of data: (1) performance metrics from pre- and post-test recordings and (2) self-reflection journals submitted weekly over the 8-week intervention.

Within-Case Analysis

Quantitative strand

Pre- and post-test speaking samples followed the official VSTEP format and were analyzed using the ELSA Speech Analyzer, a tool built on the Automatic Speech Evaluation (ASE) framework. It transcribes the recordings and gives feedback on three key areas: pacing (how fast the speaker talks), pausing (timing and rhythm), and hesitation (use of fillers or speech interruptions). These measures combine into one overall fluency score, shown as a percentage (e.g., 78% = Advanced). Since the study involved only three participants, results were explored through descriptive comparisons rather than statistical analysis. The focus was on identifying visible patterns of change between the two tests.

Although ELSA's scoring process is not fully transparent, the feedback it gives is closely tied to established ideas of utterance fluency, especially speech rate, pause control, and breakdowns in flow (Segalowitz, 2010; Tavakoli & Hunter, 2018). A student might earn a high fluency score by speaking steadily and with few hesitations, even if their speech rate is relatively slow.

Qualitative Strand

Each learner submitted one self-reflection journal per week during the 8-week period, resulting in 24 entries. These narratives were analyzed thematically following Braun and Clarke's (2006) six-phase procedure: familiarization, coding, theme generation, theme refinement, naming, and interpretation. Thematic coding focused on cognitive, emotional, and strategic responses to Copilot use. Themes included learner confidence, feedback perception, coping with errors, and motivation to continue speaking.

Cross-Case Analysis

After each case was individually analyzed, a cross-case synthesis was conducted to identify commonalities and divergences among the three learners. Shared experiences included increased willingness to speak, appreciation for real-time feedback, and reduced anxiety over time. However, the nature of improvement varied by proficiency. Specifically, the beginner (P3) prioritized overcoming hesitation and building full-sentence output. The pre-intermediate learner (P2) developed faster response times and greater fluency. The intermediate learner (P1) focused on fine-tuning phrasing, tone, and spontaneity. This comparative approach allowed the study to move beyond isolated outcomes and present a broader picture of how AI-assisted speaking practice interacts with learner readiness.

Validity, Reliability, and Trustworthiness

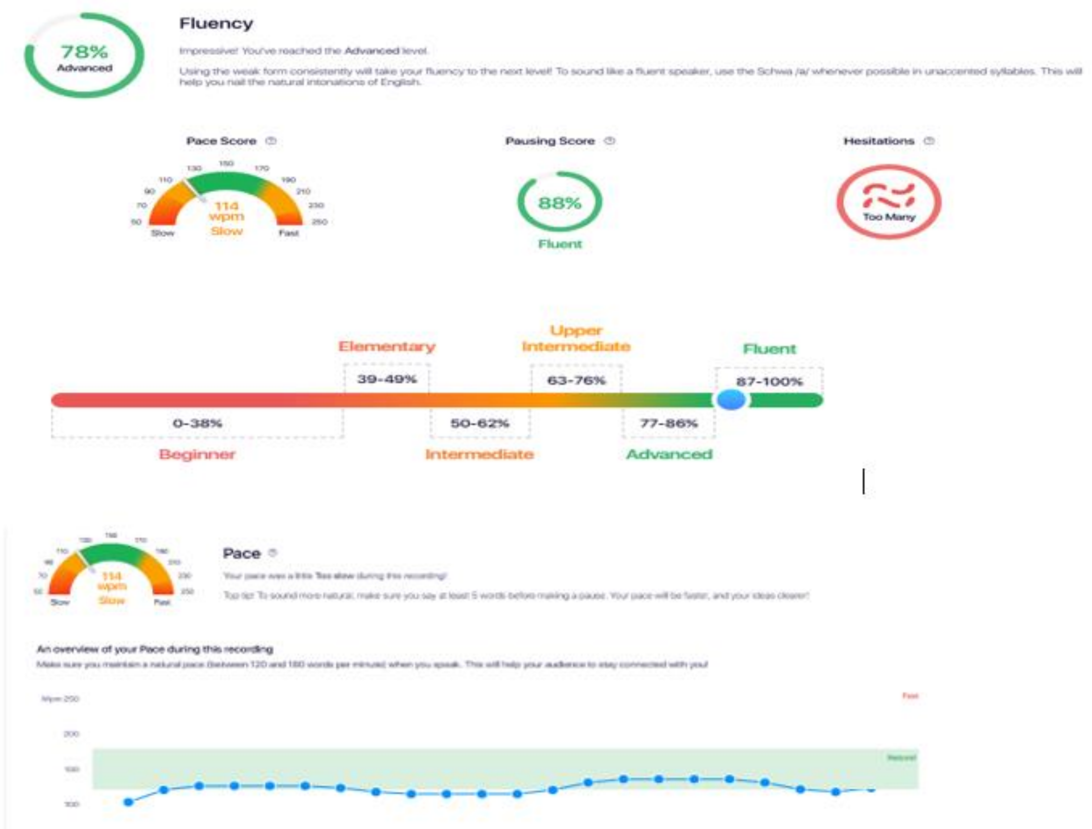
Several steps were taken to ensure credibility. First, data triangulation combined pre–post quantitative scores with qualitative reflections. Thematic analysis followed Braun and Clarke's six-step procedure, with a second coder reviewing themes to enhance reliability and reduce bias. Detailed case descriptions were included to help readers understand the context and apply the findings to similar settings. To strengthen the analysis, the ELSA Speech Analyzer was used.

Anguera et al. (2023) found a strong correlation (r = .897) between ELSA scores and expert IELTS ratings, supporting its validity for assessing L2 fluency.

By looking at specific features like pacing, pausing, and hesitation, alongside overall fluency scores, the analysis gave a clearer picture of learners' speaking performance. For example, although one participant spoke slowly (114 wpm) and showed frequent hesitations, a high pausing score (88%) and consistent rhythm yielded a strong fluency rating (78%, Advanced) (see Figure 3). This suggests ELSA prioritizes delivery quality over mere speed, supporting its alignment with utterance fluency constructs.

Figure 5.

Example of ELSA Speech Analyzer Output Showing Subcomponent Contribution to Fluency Score



Results/Findings and discussion

Quantitative Results: Utterance Fluency Development

This study examined utterance fluency development across three participants at beginner, pre-intermediate, and intermediate proficiency levels. Fluency was assessed using the ELSA Speech Analyzer, which generates both an overall fluency score and subcomponent scores that align with established definitions of utterance fluency (Segalowitz, 2010; Tavakoli & Hunter, 2018): speech rate (syllables per minute), pause frequency (pauses per minute), and hesitation frequency (e.g., filled pauses, repetitions, self-repairs). These indicators were extracted from pre- and post-test recordings and are summarized in Table 1.

Table 1.

Utterance fluency measures before and after Copilot intervention

Participant	Level	Test	Speech Rate	Pause Frequency	Hesitations
P1	Intermediate	Pre	165	8	6
		Post	176	5	3
P2	Pre-Intermediate	Pre	138	10	9
		Post	154	6	5
P3	Beginner	Pre	102	14	13
		Post	132	9	7

All three participants demonstrated measurable improvement across the core fluency indicators. Speech rate increased in all cases, especially for Participant 3 (beginner), who gained 30 syllables per minute. Pause frequency decreased notably for P2 and P3, indicating improved flow and planning. Hesitation frequency also dropped across the board, reflecting enhanced automaticity.

In addition to these features, the ELSA system provides three sub-scores: pacing score, pausing score, and hesitation feedback, which correspond to the temporal fluency dimensions. For example, P3 (Beginner) showed significant gains in pace and reduced breakdowns, cutting hesitations nearly in half. P2 (Pre-Intermediate) demonstrated balanced improvement in pacing and pause control. P1 (Intermediate) maintained a high speech rate while improving smoothness through fewer interruptions and cleaner phrasing. These patterns reflect the theoretical construct of utterance fluency, with different aspects developing according to learners' proficiency levels. Table 2 presents the overall fluency scores provided by the ELSA platform.

Table 2

Overall fluency scores by participant

Participant	Level	Pre-test Score	Post-test Score	Gain
P1	Intermediate	60	66	+6
P2	Pre-Intermediate	45	56	+11
P3	Beginner	24	44	+20

While inferential statistics were not applicable due to the small sample size, descriptive results indicate consistent upward trends. Notably, the beginner (P3) made the most substantial gains, suggesting that AI-based tools like Copilot may be especially effective for lower-proficiency learners. Intermediate learners, on the other hand, showed more gains in how they shaped their phrases and used intonation. These findings highlight that utterance fluency has many layers and develops differently based on each learner's needs.

Thematic Insights from Self-Reflections

Within-Case Analysis

Participant 3 (Beginner) started the program with clear signs of hesitation and low confidence. Early reflections often showed worry about building full sentences. One entry read, "*At first I was shy, but Copilot didn't judge me, so I spoke more.*" As the sessions continued, this nervousness gradually shifted into a sense of comfort and pride. P3 began to feel more capable, often noting the satisfaction of finishing thoughts without freezing. "*I learned words I didn't know before and improved my vocabulary related to daily topics*," they shared. A key reason for this progress seemed to be Copilot's forgiving setup, it let them try as many times as needed without fear of making mistakes. "*I could try again and again until I said it right. That made me brave*," they reflected. Still, there were moments of frustration. When the system didn't catch mispronounced words, it caused setbacks: "*It didn't always understand me, especially when I didn't say things clearly.*" For beginner learners like P3, small pronunciation issues can still be major obstacles when using voice-based tools.

Participant 2 (Pre-Intermediate) showed clear progress in managing fluency and pacing. At first, they relied on preparing answers in advance. But by the second week, they started speaking more freely. "*The more I spoke, the faster I responded. It felt natural after day 4*," one journal entry noted. For P2, Copilot worked like a memory booster, helping them recall words and phrases they had once learned but rarely used. "*It helped me remember expressions I learned before but forgot to use,*" they explained. This points to a shift from planned speech to more automatic use. P2 also valued the quick feedback on pronunciation, especially with word endings and final sounds. Still, the experience wasn't without issues. When the app paused or lagged, it broke their focus. "*Sometimes Copilot is delayed or stopped, and it broke my idea,*" they wrote. These small glitches disrupted the flow and highlighted the importance of smooth performance for fluency practice.

Participant 1 (Intermediate) took a more reflective approach. They used Copilot to fine-tune how they expressed ideas and test different word choices. Their focus was more on accuracy than confidence. "*I found better words to say what I wanted, less simple, more accurate*," one note stated. They often mentioned that Copilot's suggestions helped them sound more natural, especially when speaking about complex or personal topics. For example, they changed "good" to "memorable" after a Copilot suggestion, showing a shift toward richer vocabulary. However, P1 also noticed the tool's limits. "*It is helpful, but sometimes it feels like it does not fully understand complex ideas*," they said. As their fluency grew, they wanted deeper interaction, something the tool couldn't fully offer. For P1, the challenge had moved beyond basic fluency to meaningful conversation, a level that current AI tools still struggle to support well.

Cross-Case Synthesis: Patterns and Divergences in Fluency Development

All three participants made progress in oral fluency, but their paths differed depending on their starting levels. A shared outcome across cases was vocabulary development, though it took different forms. For Participant 3 (Beginner), vocabulary growth felt like daily discovery. As she put it, "*Every session had new words for me… it felt like I could say more things every day*." Her comment reflected not only learning but growing confidence in speaking.

Participant 2 (Pre-Intermediate) saw vocabulary not as new, but as reawakened. "*Some words I forgot came back when I practiced speaking with Copilot*," they wrote. This shows how Copilot supported lexical recall, an important bridge between knowing a word and being able to use it. For Participant 1 (Intermediate), the focus shifted again, this time toward style and naturalness: "*I started replacing simple words with more natural expressions. I wanted to sound less textbook."* For P1, fluency wasn't about adding more words but choosing better ones. Together, these reflections suggest Copilot helped learners at different stages, from basic word use to more refined expression.

Fluency confidence also developed in different ways. P3 started off hesitant but slowly became more willing to speak: "*At first, I didn't dare to speak long. Later, I kept trying until I could say what I meant.*" P2 described moving from careful planning to more spontaneous talk: "*I noticed I could respond quicker, even when I didn't plan my answer.*" P1, who already spoke fluently, became more focused on delivery: "*I realized how some pauses made me sound less fluent, so I tried to fix that.*" These shifts, from building output to speaking more freely, to polishing delivery, reflect known stages in second language fluency development.

All three viewed Copilot as a helpful and responsive partner, though in different ways. For P3, its strength was being nonjudgmental: "*If I made a mistake, I just said it again. No one laughed.*" P2 valued the instant corrections: "*It showed me what to fix right away, so I didn't keep making the same mistake.*" P1 used it to experiment with phrasing: "*I tested how to say things differently and noticed which version sounded better.*" These examples show that Copilot worked as a flexible support, allowing each learner to use it in a way that suited their goals.

Still, some challenges were shared. For P2 and P3, speech recognition errors caused frustration. P2 said, "*Sometimes I said it correctly, but it still didn't get it. I had to say it again and again.*" These issues were more noticeable for lower-level learners, whose unclear sounds or hesitations may have caused misreads. P1, however, had a different concern. "*It asked questions after my answers, but they were kind of basic, not enough to push my thinking,*" they noted. While Copilot did offer follow-up prompts, they often lacked depth. This suggests that as learners grow more advanced, they expect richer, more thoughtful conversation. If AI tools can't meet that level, their usefulness may decline.

Taken together, these cases highlight an important teaching point: one AI tool can support different learners, but how much it helps depends on how well its features match learner needs. For P3, Copilot built confidence and helped expand vocabulary. For P2, it sped up responses and supported word recall. For P1, it allowed fine-tuning, but also revealed limits in conversation quality. Despite these challenges, all three appreciated Copilot's quick feedback, ease of use, and stress-free space to speak. Moving forward, tools like this will need to grow more flexible and responsive, especially for learners aiming to think deeply and speak with greater complexity.

Discussion

This study explored how three Vietnamese EFL learners, at beginner, pre-intermediate, and intermediate levels, used Copilot, a free AI-powered tool for speaking practice. Using a multiple-case study design, the research showed that learners' proficiency levels influenced both how they benefited from the tool and where its limits became clear.

With-in cases

For the beginner, Copilot served as a tool to build confidence. The chance to repeat answers without fear of judgment helped ease speaking anxiety, similar to what Warman et al. (2023) found with introverted learners. This reflects Krashen's (1982) idea of the affective filter and supports earlier findings by Chen (2024) and Wu & Huang (2025), who also noted emotional benefits in AI-supported learning. However, frequent recognition errors disrupted communication, showing how technical issues can be especially challenging for lower-level learners.

The pre-intermediate learner used Copilot to boost fluency. Like Qiao and Zhao's (2023) findings with Duolingo, AI helped bring back forgotten words and speed up responses. Still, the voice-based format sometimes caused delays or confusing prompts, adding mental load that text-based tools often avoid.

At the intermediate level, the focus was on refining how things were said. Copilot's suggestions helped improve phrasing, aligning with Boers et al. (2006) and Hougham et al. (2024) on the value of using more varied language. Yet, as Fathi et al. (2025) also noted with Google Assistant, the tool's limited ability to hold deeper conversations left more advanced learners wanting richer, more responsive interaction.

Cross-Case Synthesis and Broader Contributions

In brief, each learner used Copilot in a way that matched their level and learning needs. For the beginner, it provided a low-pressure space to build confidence and speak with less hesitation. The pre-intermediate learner used it to bring back forgotten vocabulary and produce more fluid speech. The intermediate participant focused on polishing how they expressed ideas. These patterns reflect Vygotsky's (1978) concept of the Zone of Proximal Development (ZPD) and suggest that when AI tools fit the learner's level, they can support steady progress.

Such varied outcomes reinforce Tavakoli and Hunter's (2018) view of fluency as multidimensional. While some gains were visible in pacing, others emerged in phrasing or rhythm, echoing Suzuki and Kormos's (2022) fluency distinctions.

Emotional benefits were also consistent. All three reported less anxiety and greater speaking ease, echoing Jeon et al. (2023). Still, Copilot's technical shortcomings, especially misrecognition and repetitive prompts, reminded users of the gap between accessibility and functional depth (Nguyen & Pham, 2022; Duong & Suppasetseree, 2024). As Suzuki and Kormos (2021) suggest, understanding learner–tool interaction may offer more insight than evaluating features alone.

Theoretical and Practical Implications

The findings support key theories in L2 acquisition. Copilot's repetitive prompts and immediate feedback align with DeKeyser's (2001) automaticity framework and Sweller's (1988) Cognitive Load Theory, particularly for beginners who benefit from frequent, low-pressure practice. However, as learners become more proficient, the static, scripted nature of Copilot reveals limitations. To fully support communicative competence, AI tools should evolve towards more responsive, context-sensitive interactions.

Pedagogically, the study underscores the need to align AI use with learner profiles. All participants gained from Copilot's environment, but in different ways, from reducing anxiety to improving lexical precision. This supports Tomlinson's (2017) call for differentiated instruction. For beginners, brief Copilot sessions paired with sentence stems or visual cues can ease anxiety and support initial lexical growth. Pre-intermediate learners may benefit from timed speaking tasks or lexical retrieval, reinforced by classroom reflection or peer teaching. At the intermediate level, Copilot can foster experimentation, though it should be supplemented by richer activities, such as discussion forums or personalized feedback, to avoid plateauing. Institutionally, Copilot's free, browser-based format offers an accessible option for Vietnamese universities. Yet meaningful implementation requires teacher orientation, digital training, and integration into broader frameworks like task-based or flipped instruction (Hockly, 2018).

Used effectively, Copilot can also aid formative assessment. Teachers may review learner journals or recordings to track fluency development and tailor support. Rather than viewing AI as a replacement for instruction, this study positions tools like Copilot as adaptable extensions of pedagogy ones that, when integrated thoughtfully, can enrich learning across proficiency levels.

Limitations and Future Directions

This study's insights are limited by its small sample and focus on a single AI tool. Broader studies across learner backgrounds, including gender and digital literacy, are needed to generalize findings. Longitudinal research could also reveal whether fluency gains persist beyond initial novelty. Future comparisons with more immersive or emotionally responsive platforms may clarify which tools best suit different learner needs.

A key barrier remains technical reliability. Participants, especially at lower levels, were discouraged by frequent voice recognition errors. These disruptions affected confidence and fluency. Further work should examine how such breakdowns influence motivation and explore whether built-in scaffolds, such as pronunciation support, can reduce frustration and sustain engagement.

Conclusion

This study explored how Copilot, a free AI-based speaking tool, supports L2 fluency development among Vietnamese EFL learners at varying proficiency levels. Pre–post fluency measures and reflective journals showed that Copilot provided a low-pressure, accessible space for regular speaking practice, especially benefiting lower-level learners with limited real-world exposure. While all participants improved in fluency and confidence, their progress differed based on linguistic readiness and goals, highlighting the need for differentiated AI integration. Technical limitations, such as misrecognition and limited dialogue flexibility, revealed trade-offs between accessibility and communicative depth. Although the small sample and short duration limit generalizability, the study contributes practical insight into how lightweight AI tools can enhance speaking instruction when thoughtfully embedded. Future research should examine long-term effects, refine technical performance, and evaluate broader implementation across diverse contexts. While AI cannot replicate human interaction, tools like Copilot can meaningfully supplement instruction and expand access to speaking opportunities in EFL education.

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