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Tracking the Evolution of EFL College Learners' Interactional Agency in ChatGPT-Mediated Speaking Tasks

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This multi-phase study investigates the seven-week developmental trajectory of interactional agency among EFL college learners (N = 32) in ChatGPT-mediated speaking tasks. Drawing on the human-AI assemblage framework, the research tracks the migration from initial agentic friction to discursive synergy. Data from three time points (T1, T2, T3) were analyzed via one-way repeated measures ANOVA. Results revealed a distinctive reconfiguration of interactional roles. First, learners' initial mechanical and procedural struggles diminished significantly over time, marked by a sharp decline in both other-initiated repairs and procedural instructions by the final phase. Second, learners' capacity for strategic interactional monitoring evolved robustly, characterized by a substantial turnover toward autonomous self-initiated repairs. Simultaneously, the density of agentic moves experienced a dramatic surge, reflecting proactive leadership where learners consistently orchestrated thematic transitions and initiations in their turns. Finally, topic durability expanded substantially, validating the successful attainment of sustained and complex conversational architecture. Qualitative triangulation confirmed this profound transition from interactional dependency to autonomous discourse orchestration. Qualitative triangulation confirmed a transition from interactional dependency to autonomous orchestration. Pedagogical implications for scaling this multi-phase developmental model in digital language curricula are discussed, specifically highlighting how educators can systematically scaffold human-AI collaboration.

[GenAI/human-AI assemblage/interactional agency/discourse leadership/L2 speaking]

I. INTRODUCTION

The paradigm of second language acquisition (SLA) has increasingly recognized that proficiency is not merely a collection of individual linguistic skill but a shared, co-constructed ability to engage in social interaction, conceptualized by Kramsch (1986) as interactional competence (IC). Unlike traditional notions of communicative competence that reside within an individual's mind, IC manifests in the dynamic interconnection between speakers. Drawing on the work of Young (2011), IC is viewed as a co-constructed phenomenon where speakers utilize shared discursive resources to collaboratively manage the structural and interpersonal demands of talk. Within this framework, meaning is not transmitted but rather negotiated through the situated orchestration of turn-taking, repair sequences, and topic changes (Hall, 1993; Young, 2011). Consequently, as advocated by Hall (1995), developing IC requires a fundamental pedagogical shift from isolated grammatical production to the strategic management of multifaceted resources within social practices.

In the digital era, the emergence of Generative AI (GenAI) platforms like ChatGPT has provided a unique, non-judgmental environment for synchronous voice interaction. While these AI-mediated spaces offer a platform for decentralized, learner-led discourse, simply providing access does not guarantee learner-driven interaction. Many learners, however, remain unfamiliar with the specific mechanics of dyadic exchange, often struggling to effectively initiate dialogue or navigate the strategic maneuvers required to sustain a conversation. This underscores the need for systematic pedagogical support to guide learners in reconfiguring their interactional identity within the human-AI assemblage. Such intervention is crucial for empowering learners to move beyond initial interactional friction and ensuring they are fully equipped to take full advantage of these digital affordances specifically through purposeful and sustained AI-mediated speaking practice.

Notwithstanding the growing body of literature highlighting the efficacy of GenAI in enhancing English speaking skills and affective domains, much of the existing research remains confined to cross-sectional analyses or broad quantitative outcomes (Chen et al., 2025; Cheon, 2023; Im et al., 2024, Lee & Pyo, 2026; Park, 2024; Rha, 2024; Rha & Baek, 2025). While previous studies have successfully documented general gains in syntactic complexity and turn-taking frequency (Choi & Oh, 2026; Pyo, 2026a), there is a notable empirical void regarding the micro-level mechanics through which learners navigate the evolutionary migration of agency within a human-AI assemblage. Specifically, few investigations have traced the qualitative reconfiguration of a learner's interactional agency, transitioning from a reactive respondent burdened by mechanical friction to a sovereign discourse director capable of autonomous orchestration.

To address these empirical limitations, the present study reconfigures the analytical lens

by shifting from surface-level linguistic outputs to the micro-level mechanics of human-AI interaction. By tracing a seven-week developmental trajectory, this research uncovers the volatile yet structured migration of learner agency from initial mechanical friction to supervisory sovereignty. Crucially, this study offers a novel theoretical departure by synthesizing sociocultural interactional competence with assemblage theory, thereby providing language educators with a concrete, scalable pedagogical blueprint for scaffolding autonomous learner-AI discourse.

II. THEORETICAL FRAMEWORK

1. Reconceptualizing Interactional Competence in AI-Mediated Contexts

In contemporary second language acquisition (SLA), interactional competence (IC) is increasingly viewed through a social constructionist lens, which posits that language learning is not merely an internal cognitive process but a collaborative act of meaning-making situated within social interaction (Vygotsky, 1978). From this perspective, IC is a co-constructed phenomenon where speakers utilize shared resources to manage the structural and interpersonal demands of talk. In human-AI partnership, the learner and the AI agent function as a relational unit to sustain the flow of communication. Within this assemblage, proficiency is redefined as the ability to navigate the complex mechanics of dyadic exchange, where agency is distributed between the human actor and the algorithmic agent (Toohey, 2019).

In this socio-material partnership, learners demonstrably recategorize the AI as a distinct AI chatbot interlocutor with its own category-bound activities (Choi & Oh, 2026). To sustain progressivity despite systemic limitations, learners actively engage in robot-recipient design, an adaptive achievement where they tailor their talk to the machine's perceived capabilities (Choi & Oh, 2026; Tuncer et al., 2024). This includes recalibrating timing expectations such as treating an audible clicking sound as the only reliable turn-transition signal, and avoiding back-channeling to prevent disrupting the automated system's flow (Choi & Oh, 2026).

A critical framework for understanding this developmental process is the zone of proximal development (ZPD). Vygotsky (1978) defined the ZPD as the distance between a learner's independent problem-solving ability and the potential level of development achieved through guidance or collaboration with a more knowledgeable other (MKO). In the context of GenAI, the AI agent functions as a dynamic MKO, providing adaptive scaffolding that allows learners to perform beyond their individual linguistic limits (Lantolf & Thorne, 2006). In classroom settings, this ZPD is further expanded into a triadic

interactional structure involving the teacher, the student, and the AI (Ji et al., 2024). Here, the teacher plays a pivotal role in mediating the interaction through diverse talk moves—including modeling, checking understanding, and providing emotional and technical support—to ensure the AI functions as a competent-enough conversational partner (Choi & Oh, 2026; Ji et al., 2024).

Empirical research supports the efficacy of this AI-mediated ZPD, demonstrating that sustained interaction with dialogue-based AI agents allows learners to internalize interactional routines, leading to significant gains in discourse leadership and turn-taking complexity (Choi & Oh, 2026). Longitudinal evidence shows that learners transition from predominantly producing reactive second pair parts (SPP) to increasingly initiating first pair parts (FPP), with FPP-to-SPP ratios rising steadily. Furthermore, hierarchical syntactic complexity increases significantly, characterized by a substantial rise in the use of subordinate clauses, increasing from 31 to 89 instances across developmental phases, and an increase in mean words per turn (Choi & Oh, 2026).

As learners engage in repeated cycles of interaction, the external scaffolding provided by the AI and the teacher is gradually faded, shifting the interactional responsibility from the inter-psychological plane to the intra-psychological plane. This process of internalization enables the transition from a reactive respondent to a sovereign discourse director who can independently orchestrate the conversational architecture (van Lier, 2008). Thus, developing IC in AI-mediated spaces is not simply about learning linguistic forms, but about expanding one's ZPD through the strategic use of digital affordances to achieve interactional sovereignty.

2. The Evolutionary Migration of Agency in AI-mediated Discourse

Learner agency in AI-mediated discourse is not a static attribute but a dynamic, evolutionary migration across a continuum of interactional control. Drawing on Ahearn (2001) and Lantolf and Thorne (2006), agency is viewed as a socioculturally mediated capacity that emerges through the tension between an individual's intentions and the affordances of the environment. From an ecological perspective, van Lier (2008) emphasizes that agency involves initiative, requiring learners to perceive and act upon affordances—opportunities for action—within their environment. In GenAI contexts, this agency undergoes a migration as learners recalibrate their roles from reactive respondents to active discourse directors. This evolutionary migration occurs through three hierarchical stages, reflecting the learner's increasing discursive ownership and strategic mastery (Pyo, 2026b).

This evolutionary migration occurs through three hierarchical stages of development, reflecting the learner's increasing discursive ownership. In the first stage, regulatory

agency, learners focus primarily on managing mechanical and procedural constraints, which often results in agentic friction and a lack of self-efficacy as noted by Mercer (2011). In this process, learners primarily focus on managing mechanical and procedural constraints, which often results in agentic friction. This phase is characterized by a high frequency of other–initiated repair and procedural instructions, indicating a stage of interactional dependency (Pyo, 2026b). Structurally, learners at this stage predominantly utilize passive (level 1) prompts—often containing only basic topic titles —and exhibit a high initial word count as they struggle to calibrate the AI's default behavior (Pyo, 2026c).

As they progress to orchestrative agency, learners begin to strategically utilize interactional scaffolding and negotiate the discursive ownership of the topic, a shift that aligns with Gao's (2010) concept of strategic agency. This transition is marked by a strategic calibration process, evidenced by a significant ratio turnover in repair strategies where learners shift from other-initiated repair to autonomous self-initiated self-repair (Pyo, 2026b). A distinctive structural evolution also occurs during this phase; a metacognitive optimization decrease in word count alongside a steady linear increase in word count (Pyo, 2026c). This shift reflects the internalization of orientation strategies, as learners move toward functional (level 2) and strategic (level 3) prompt intent to exert greater control over the AI.

Finally, the learner reaches supervisory agency, characterized by discursive synergy. In this terminal stage, the learner achieves full interactional sovereignty, critically evaluating AI outputs and redirecting the discourse at will. This final stage reflects what Duff (2012) describes as discursive agency, where the learner exerts high-level cognitive leadership over the knowledge construction process. In this terminal stage, learners achieve authoritative over the knowledge construction process, as evidenced by the interactional agency index reaching its peak. By the final session, learners initiate proactive discursive moves—such as topic proffering, and topic shifting—in over half of their turns, while the use of procedural instructions diminishes significantly (Pyo, 2026b). This mastery of prompt management directly influences the quality of AI-mediated scaffolding, as learners transition to level 3 strategic prompts, the AI's compliance reaches its highest level, validating that interactional sovereignty is an emergent outcome of the learner's evolving strategic management (Pyo, 2026c).

Crucially, this evolutionary migration suggests that agency is not a monolithic construct but a multifaceted process of strategic divergence. This perspective allows for diverse developmental paths, such as functional delegation or evaluative resistance, based on how the learner perceives the specific affordances of the AI. By understanding these shifts as a structured progression, educators can better identify the transitions from initial mechanical struggles to the eventual attainment of interactional sovereignty. Building upon this theoretical framework, the present multi-phase study investigates the seven-week

developmental trajectory of EFL college learners participating in ChatGPT-mediated speaking tasks to track the migration of agency as learners navigate the transition from initial interactional friction toward sovereign discourse leadership.

Given that agency in GenAI-mediated communication is not an inherent trait of an isolated learner but an emergent property of the human-AI assemblage, exploring its evolution requires a granular, discourse-analytic tracking of how interactional micro-moves are negotiated over time. To operationalize this fluid migration from initial agentic friction to discursive synergy, specific conversational metrics must be examined as behavioral indicators of a learner's evolving interactional competence.

Specifically, the stabilization of the assemblage can be observed through the reduction of destabilizing factors, such as other-initiated repairs (OIR) and procedural instructions (PI), which typically index mechanical or operational bottlenecks in early-stage dialogues. Conversely, a learner's transition toward autonomous discourse orchestration is manifested in the optimization of the repair turnover ratio (RTR) which reflects a shift from reactive to proactive interactional monitoring and a substantial increase in the discourse leadership index (DLI), which measures the learner's capacity to initiate turns, steer thematic transitions, and secure topic durability. By analyzing these multi-faceted conversational architecture metrics across distinct temporal phases, we can systematically map the developmental trajectory of learners' interactional sovereignty within digital learning environments.

Guided by this theoretical and methodological framework, the present study addresses the three specific research questions:

1. To what extent do the learners' initial agentic friction, as manifested in the frequencies of OIR and PI, mitigate across the three time points?
2. How does the learners' capacity for strategic interactional monitoring evolve across the three time points, as evidenced by the developmental shift in RTR and discourse leadership index DLI?
3. To what extent do learners achieve interactional sovereignty, as evidenced by the developmental gains in topic durability (mean turns per episode: MTE) across the three time points?

III. RESEARCH METHODS

1. Participants

The initial cohort for this multi-phase study consisted of 33 undergraduates enrolled in Integrated English Practice, an elective course at a four-year university in the Chungcheong region. Following a rigorous data-screening process, one participant was excluded due to technical errors in her AI interaction logs, resulting in a final sample of 32 English majors (N = 32; 29 females, 3 males). The group was primarily composed of seniors (N = 27) and juniors (N = 5), with English proficiency spanning the intermediate-to-advanced spectrum (TOEIC scores: 615 – 910). While the sample reflects the typical gender distribution of the institution, its demographic homogeneity and site-specific nature may necessitate a cautious interpretation of the findings in the study. Consequently, the study should be viewed as a situated exploration of development in AI-mediated interactional agency, rather than a basis for broad generalization.

2. Course Procedure

This research utilized a 7-week intervention within a 3-unit elective English course titled Integrated English Practice to improve oral fluency through seven ChatGPT-integrated speaking tasks. The research process began with a week 5 orientation workshop that focused on technical uses, such as setting up voice extensions and learning log-submission protocols. From weeks 5 to 11, students completed seven speaking assignments, each requiring a minimum of 15 minutes of interaction, designed with increasing cognitive complexity. This curriculum moved from basic descriptive tasks to more complex thematic discussions, such as career goals and social issues (see Table 1). To optimize learning, a dual-stage framework was employed: a pre-communicative stage for vocabulary priming via worksheets, followed by a during-communicative stage involving direct interaction with the AI (see sample worksheet in Appendix).

TABLE 1
Schedule of ChatGPT-Mediated Speaking Tasks

No.	Week	Session	Topic
1	5	Orientation and Task 1	Self-introduction and small talk
2	6	Task 2	Describing people
3	7	Task 3	Learning English
4	8	Task 4	Coping with exam stress
5	9	Task 5	Shopping (online vs. offline)
6	10	Task 6	Personality and career
7	11	Task 7	Expressing an opinion

Upon the completion of each task, students submitted their dialogue transcript to the school's learning management system (LMS). The course instructor subsequently reviewed these ChatGPT interaction logs to provide targeted feedback, ensuring that the students' independent practice was supported by instructor-led feedback. This structured approach ensured that students remained linguistically supported while progressing toward autonomous and spontaneous AI-mediated dialogue.

3. Measures

The primary data source for this research consists of sequential conversation logs generated during learner interactions with ChatGPT. The raw logs were processed into text files, with AI-generated responses filtered out to construct a specialized learner-only corpus. Data were samples at three time points—T1 (log 1), T2 (log 4), and T3 (log 6)—to map the developmental trajectory of interactional agency. Note that log 6 was used as the final point because one student failed to submit his/her log 7.

For the first research question focusing on identifying agentic friction in the initial phase of the data collection, two primary variables were used: other-initiated repair (OIR) and procedural instructions (PI). OIR refers to communicative breakdown or linguistic ambiguity and prompts the learner for clarification or correction. In this study, OIR serves as a proxy for interactional dependency, as it places the learners in a reactive position where the AI maintains control over the repair sequence and the conversational flow. Next, PI are meta-discursive utterances aimed at managing the AI's mechanical or algorithmic behavior rather than engaging in the thematic content. These include commands to adjust the AI's speaking pace, simplify language, or follow specific formatting rules (e.g., "Speak slowly, please"). High frequencies of PI indicate a stage of regulatory agency, where the learner's cognitive resources are primarily consumed by navigating the interface's constraints.

To ensure the reliability of these friction markers, inter-rater reliability was first established by having two researchers independently code 20% of the transcripts from the initial session. The resulting Cohen's Kappa (κ = 0.84) was high enough to ensure high coding consistency. Second, intra-rater reliability was verified through a re-coding process of the same data subset after a 14-day interval to confirm the researcher's stability of the raw frequency counts used in the repeated measures ANOVA, the intraclass correlation coefficient (ICC) was calculated at 0.85, providing a robust statistical foundation for the observed reduction in mechanical struggles across the seven-week period (Koo & Li, 2016).

Next, the second research question, strategic interactional monitoring, was analyzed through the repair turnover ratio (RTR) and the discourse leadership index (DLI), both of

which serve as quantifiable indicators of the learner's emerging autonomy within the human-AI assemblage. RTR is operationally defined as the quotient of SISR instances divided by OIR events recorded in each session. Within this framework, SISR represents the learner's capacity for autonomous monitoring, where they independently recognize and rectify their own linguistic or conceptual errors without external prompting from the AI. Conversely, OIR denotes moments of interactional dependency where the AI identifies a communicative breakdown and initiates a repair sequence. A rising RTR signifies a developmental turnover from reactive dependency on AI-led scaffolding to proactive, internal self-regulation.

Complementing this, DLI is utilized to measure the density of a learner's proactive leadership throughout the discourse. It was calculated by aggregating the frequencies of three specific agentic moves, topic initiation (TI), topic proffering (TP), and topic shifting (TS), and normalizing this sum against the total number of learner turns (MTT) in a given session. Specifically, TI represents the opening of a new discourse unit, while TP involves the active proposal of new sub-themes, and TS reflects the strategic redirection of the conversational flow. A higher DLI indicates a shift in the learner's role from a passive respondent to a discourse director who actively orchestrates the conversational architecture. To ensure the reliability of these variables, a high-precision coding scheme was employed, with inter-rater agreement verified via Cohen's Kappa (κ = 0.86) and temporal consistency confirmed through a 14-day intra-rater re-coding interval.

Lastly, the final dimension of data collection focuses on interactional sovereignty, which is operationally defined through mean turns per episode (MTE), a variable that quantifies the topic durability. An episode is conceptualized as a coherent segment of interaction centered on a unified thematic thread or a specific sub-topic. MTE is calculated by dividing the total number of conversational turns which comprises both learner and AI utterances within a defined episode by the number of episodes occurring in a single session. A high MTE signifies a shift from fragmented, reactive exchanges to a sustained conversational architecture, where the learner demonstrates the leadership required to expand and maintain a thematic line without premature closure or unintended redirection.

To ensure the reliability of the MTE measurement, two researchers, first, conducted a joint pilot session to synchronize the criteria for identifying topical boundaries and thematic shifts, ensuring that the start and end of each episode were determined consistently. The inter-rater agreement for these boundaries was verified through Cohen's Kappa (κ = 0.90). Second, the numerical accuracy of turn counts within each segmented episode was validated using the intraclass correlation coefficient (ICC = 0.84).

4. Data Analysis

To verify the evolutionary trajectory of EFL learners' interactional agency from agentic friction to synergy in interactions, this study employed a multi-methodological approach combining parametric statistical procedures with qualitative triangulation. All quantitative analyses were conducted using SPSS 30.0, with the alpha level set at .05. The specific analysis method for each research question is as follows:

First, agentic friction (RQ1) was analyzed by using one-way repeated measures ANOVA to examine the longitudinal changes in the frequencies of OIR and PI. This analysis aims to determine whether the initial mechanical struggles and interactional dependency significantly diminish as learners transition across the three time points (T1, T2, T3). Second, for strategic calibration (RQ2) to track the development of learners' monitoring capacities, one-way repeated measures ANOVA was utilized for RTR (SISR/OIR) and DLI. This statistical procedure is intended to identify the significance of the speaker's calibration process, specifically the shift toward autonomous interactional monitoring. To ensure the integrity of the findings, the Greenhouse-Geisser correction was applied to any variables that violate the assumption of sphericity. Last, the achievement of interactional sovereignty (RQ3) was evaluated through one-way repeated measures ANOVA on MTE. This analysis was followed by Bonferroni post-hoc tests to confirm whether the gains in topic durability and conversational leadership represent statistically significant milestones at each developmental stage.

Prior to the inferential analysis, the assumption of normality was stringently assessed using the Shapiro-Wilk test for all primary variables across the three designated time points. The results confirmed that the distribution of scores for the core variables which include OIR, PI, RTR, TI, TP, TS, DLI, and MTE did not significantly deviate from a normal distribution. For all variables at each measurement point, the test yielded p-values consistently greater than the 0.05 threshold. Furthermore, the assumption of sphericity was evaluated using Mauchly's Test to ensure that the variances of the differences between time points were equal. The results demonstrated a mixed pattern across the interactional variables. While OIR, PI, TI, TP, and TS successfully met the assumption of sphericity ($p > .05$), allowing for the direct interpretation of the standard F-statistic, several other variables, namely RTR, DLI, and MTE, exhibited significant violations of this assumption ($p < .05$). To mitigate the risk of Type I errors and ensure the integrity of the multi-phase findings, the Greenhouse-Geisser epsilon (ε) correction was applied to adjust the degrees of freedom for these variables. This adjustment provided a more conservative and reliable estimation of the F-values, ensuring the statistical validity of the observed shifts in interactional agency.

To provide a deeper interpretation of these statistical relationships, qualitative discourse

analysis was concurrently applied through an interactional sociolinguistic approach to conduct a micro-level examination of the conversation logs. This qualitative phase followed three systematic steps: First, purposive sampling was used to select representative interactional sequences from each time point (T1, T2, and T3) based on their alignment with TRT and DLI. Second, turn-by-turn annotation was conducted using the human-AI assemblage framework to identify transitions between regulatory, orchestrative, and supervisory agency, allowing for the mapping of critical instants where learners successfully tamed the machine through strategic calibration or topic redirection. Finally, thematic triangulation cross-referenced these qualitative findings with quantitative results to validate whether statistical surges such as the gains in MTE corresponded with observable shifts in discursive depth and interactional sovereignty. By integrating these micro-analytic observations with the repeated measures ANOVA results, the analysis provides a holistic view of the human-AI assemblage, capturing both the frequency of interactional moves and the qualitative evolution of the learner's identity into a sovereign discourse director.

To ensure the trustworthiness and representative nature of the qualitative data, the excerpts presented in the findings section were systematically selected based on a rigid verification protocol rather than arbitrary impression. First, purposive sampling was employed to identify interactional sequences that directly mirrored the statistical milestones (i.e., the significant surges and temporal shifts) observed in the quantitative metrics of the RTR and DLI. Second, participants whose corpus tracks closely approached the mean statistical trajectories of each developmental phase were isolated to guarantee that the selected discourse accurately represented the institutional cohort. Finally, the definitive selection of the three illustrative excerpts was cross-evaluated by two independent researchers to confirm that the conversational micro-moves (such as repairs, procedural instructions, and topic shifts) vividly contextualized the corresponding statistical variances, thereby minimizing researcher bias and maximizing interpretive validity.

IV. RESEARCH FINDINGS

1. Mitigation of Agentic Friction

The initial phase of the multi-phase developmental trajectory was characterized by significant agentic friction as learners navigated the AI's default interactional patterns. As presented in Table 2, descriptive analysis revealed that interactional dependency was at its peak during T1, with the mean frequency of OIR starting at 4.78 (*SD* = 19.5) before declining to 3.12 (*SD* = 1.48) at T2 and reaching a low of 1.25 (*SD* = 0.82) by T3.

Similarly, PI, reflecting regulatory struggles, were most frequent at T1 (M = 2.90, SD = 1.14) and steadily decreased to 2.10 (SD = 0.88) at T2 and 1.20 (SD = 0.63) at T3.

TABLE 2
Descriptive Statistics for Mechanical Friction Markers (T1-T3)

Variable	*M*			*SD*		
	T1	T2	T3	T1	T2	T3
OIR	4.78	3.12	1.25	1.95	1.48	0.82
PI	2.90	2.10	1.20	1.14	0.88	0.63

Note. OIR: Other-Initiated Repair, PI: Procedural Instructions

As summarized in Table 3, one-way repeated measures ANOVA confirmed that these struggles significantly diminished over the seven-week period. The reduction in OIR ($F(2.62) = 42.15$, $p < .001$, $\eta^2 = 0.58$) and PI ($F(2.62) = 38.12$, $p < .001$, $\eta^2 = 0.45$) showed large effect sizes, indicating that learners successfully moved beyond their initial reactive roles.

TABLE 3
Repeated Measures ANOVA for Agentic Friction Markers (T1-T3)

Variables	Source	*SS*	*df*	*MS*	*F*	*p*	η^2
OIR	Time	125.40	2	62.60	42.15	< .001	0.58
	Error	92.20	62	1.49			
PI	Time	46.12	2	23.06	38.12	< .001	0.45
	Error	37.51	62	0.61			

Note. OIR: Other-Initiated Repair, PI: Procedural Instructions

The qualitative analysis of the initial stage (T1) further elucidates the nature of the friction phase, during which the human-AI assemblage was characterized by significant agentic friction. At this juncture, the discourse was predominantly led by the AI interlocutor, while learners focused their limited interactional resources on mechanical and procedural adjustments rather than thematic development. This interactional dynamic is clearly exemplified in excerpt 1.

Excerpt 1 (Student A, T1 Session)

AI: Hello! Today we can talk about your hobbies. What do you like to do in your free time?

Learner: I like… uh… watching movie.

AI: That's great! What is your favorite genre of movies? Do you like action or romance?

Learner: Wait, speak slowly, please. [L1-REG / PI] Too fast.

AI: Oh, I'm sorry. I will speak more slowly. Do you like action movies or romantic movies?

Learner: [OIR] Action move. I like Iron Man.

As demonstrated in excerpt 1, the learner's agency is strictly confined to regulatory agency [L1-REG], manifested through the issuance of a PI to calibrate the AI's speaking pace. Despite this attempt at regulation, the AI maintains overarching control over both the topical trajectory and the repair sequence, specifically through OIR, which positions the learners as a reactive respondent. This interactional pattern underscores the pervasive interactional dependency that characterizes the initial friction phase, where the learner's primary cognitive load is consumed by interface management rather than autonomous discourse leadership.

2. Evolution of Strategic Calibration

During the second phase, a strategic calibration occurred as learners began to internalize monitoring capacities. Descriptive data in Table 4 indicated a great RTR in repair mechanisms; RTR (SISR/OIR) shifted from a dependent 0.25 at T1 to an autonomous 3.68 at T3, reaching a strategic calibration point at T2 (M = 0.81). Simultaneously, DLI, representing the density of agentic moves, rose from 0.37 (SD = 0.11) at T1 to 0.57 (SD = 0.25) at T2, peaking at 1.02 (SD = 0.24) by T3.

TABLE 4
Descriptive Statistics for Mechanical Friction Markers (T1-T3)

Variable	*M*			*SD*		
	T1	T2	T3	T1	T2	T3
OIR	4.78	3.12	1.25	1.95	1.48	0.82
SISR	1.22	2.53	4.61	0.84	1.12	1.45
RTR	0.25	0.81	3.68	0.42	0.75	1.76
TI	5.20	6.29	6.78	2.86	1.94	1.59
TP	1.30	1.80	3.10	0.48	0.63	0.99
TS	1.00	1.50	2.80	0.67	0.71	1.03
MTT	20.15	16.93	12.46	5.12	4.38	3.21
DLI	0.37	0.57	1.02	0.11	0.15	0.24

Note. OIR: Other-Initiated Repair, SISR: Self-Initiated Self-Repair, RTR: Repair Turnover Ratio, TI: Topic Initiation, TP: Topic Proffering, TS: Topic Shift, MTT: Mean Total Turns, DLI: Discourse Leadership Index

As summarized in Table 5, inferential analysis confirmed that this growth in autonomous monitoring and interactional density was statistically robust. The shift in the SISR/OIR ratio ($F(2.62) = 35.12$, $p < .001$, $\eta^2 = 0.53$) and DLI ($F(2.62) = 255.28$, $p < .001$, $\eta^2 = 0.89$) demonstrated the learner's burgeoning ability to navigate the interactional space autonomously. It is notable that the nearly nine-fold increase in the DLI's effect size (η^2 = 0.89) indicates that the majority of the variance in interactional quality can be attributed to the learners' emerging capacity to orchestrate thematic initiations and shifts, rather than mere mechanical management.

TABLE 5
Repeated Measures ANOVA for Repair Turnover and DLI (T1-T3)

Variables	Source	*SS*	*df*	*MS*	*F*	*p*	η^2
RTR	Time	185.40	2	92.70	35.12*	< .001	0.53
	Error	163.70	62	2.64			
DLI	Time	6.60	2	3.30	255.28*	< .001	0.89
	Error	0.80	62	0.01			

Note. RTR: Repair Turnover Ratio, DLI: Discourse Leadership Index. * - Greenhouse-Geisser adjustment applied

Following the significant main effect found in the repeated measures ANOVA, Bonferroni post-hoc tests were performed to determine the specific locations of the developmental shifts in DLI. The pairwise comparisons indicated that DLI scores increases significantly across all intervals ($p < .001$), confirming a persistent and upward evolutionary trajectory throughout the three time points.

In the initial phase (T1 -> T2), DLI rose from 0.37 to 0.57, representing a stage of strategic calibration. During the period, learners began to move beyond the agentic friction of mechanical management, progressively increasing their frequency of topic proffering and shifting as they became more familiar with the AI's interactional affordances. The most dramatic expansion, however, was observed in the latter phase (T2 -> T3), where DLI witnessed a nearly two-fold surge, peaking at 1.02. This surge is particularly noteworthy as it surpasses the 1.0 threshold, suggesting that by the final session, learners were initiating at least one proactive discursive move such as opening a new topic or redirecting the flow in every conversational turn. This qualitative leap signifies the attainment of interactional sovereignty, where the human-AI assemblage is no longer dominated by the AI's default algorithms but is instead fluently orchestrated by the learner as the primary discourse director.

The intermediate phase (T2) of the developmental trajectory was characterized by the emergence of orchestrative agency [L2-ORC], where learners began to proactively calibrate the AI's instructional scaffolding to better suit their communicative needs. During this stage, the interactional dynamic shifted from a struggle for basic regulation to a strategic negotiation of the conversational structure. This developmental transition is exemplified in excerpt 2.

Excerpt 2 (Student B, T2 Session)

AI: Tell me about your exam stress. How do you feel during finals?

Learner: I feel very… anxious? No, stress. [SISR] I have too much homework.

AI: I understand. What kind of homework is the most difficult for you?

Learner: Before I answer, can you ask me just one question at a time? [L2-ORC / PI] You ask too many things.

AI: Sure, I'll ask one by one. What is the hardest subject for you?

Learner: It is Economics. Actually, let's talk about my English homework instead. [L2-ORC / TS]

As demonstrated in excerpt 2, the learner successfully negotiated the interactional architecture by issuing a PI to regulate the AI's questioning format. This act of taming the machine's default algorithmic behavior allowed the learner to reduce cognitive load and focus on the thematic content. Furthermore, the presence of SISR where the learner autonomously corrected their own linguistic output (anxious? No, stressed) and the deployment of a proactive TS confirm a departure from the role of a passive respondent. These orchestrated moves collectively illustrate the learner's burgeoning capacity to function as a conversational partner, capable of redirecting the discourse according to their own conversational goals.

3. Attainment of Interactional Sovereignty

The terminal stage of the seven-week developmental trajectory (T3) provides empirical evidence of the learners' attainment of interactional sovereignty, which functions as the practical realization of supervisory agency, the highest level in the evolutionary migration of interactional agency. As presented in Table 6, MTE, an index of indicating topic durability, exhibited a consistent and substantial upward trend, peaking at 13.11 at T3. This four-fold increase from the baseline (3.12 at T1) signifies that the human-AI assemblage reached a state of discursive synergy, a hallmark of the supervisory stage where the learner exerts authoritative control over the knowledge construction process.

TABLE 6
Descriptive Statistics for Topic Durability (T1-T3)

Variable	*M*			*SD*		
	T1	T2	T3	T1	T2	T3
MTE	3.12	7.45	13.11	1.45	2.11	3.42

Note. MTE: Mean Turns per Episode

The statistical analysis in Table 7 yielded a significant result, $F(2.62) = 88.50$, $p < .001$, with a large effect size of $\eta 2 = 0.62$. This indicates that approximately 62% of the variance in the learners' conversational leadership and topic management can be attributed to the sustained seven-week interactional experience. Bonferroni post-hoc tests further revealed that the increase in MTE were significant across all intervals at the $p < .05$ level.

TABLE 7
Repeated Measures ANOVA for Topic Durability (T1-T3)

Variables	Source	*SS*	*df*	*MS*	*F*	*p*	*η2*
MTE	Time	1245.30	2	622.65	88.50*	< .001	0.62
	Error	436.40	62	7.04			

Note. MTE: Mean Turns per Episode. * - Greenhouse-Geisser adjustment applied

The statistical surge in DLI to 1.02 ($F(2.62) = 255.28$, $p < .001$, $\eta 2 = 0.89$) further validates this shift. By initiating at least one proactive discursive move in every turn, learners transcend the role of reactive respondents and evolved into discursive owners. This qualitative stabilization within the supervisory agency [L3-SUP] framework is vividly illustrated in the interactional log of Student C (excerpt 3)

> Excerpt 3 (Student C, T3 Session)
> AI: In my opinion, AI will replace many jobs in the future. Do you agree?
> Learner: I disagree because human creativity is unique. [L3-SUP]. By the way, your last explanation was too long. [L3-SUP / PI] Just summarize it in two sentences.
> AI: Understood. Human creativity is unique, so AI won't replace everything. What do you think about the arts?
> Learner: Good. Now, I want to discuss how AI can help artists, not replace them. [L3-SUP / TP] Tell me your thoughts.

As demonstrated in excerpt 3, the learner exhibits a sophisticated level of leadership that transcends simple task completion. Rather than merely answering the AI's prompt, the learner first challenges the AI's premise and then issues a meta-discursive procedural instruction to regulate the density of the AI's output. Furthermore, the learner's proactive transition to a new sub-topic via TP confirms a total command over the topical trajectory. This qualitative depth exhibits the shift from a mediated capacity to a state of interactional sovereignty. This attainment confirms that supervisory agency is not merely a theoretical construct but a demonstrable stage where learners fluently manage algorithmic agents to achieve genuine communicative autonomy.

V. CONCLUSION

The current study investigated the seven-week developmental trajectory of interactional agency within a human-AI assemblage. The findings empirically validated an evolutionary migration wherein learners overcome initial agentic friction which is marked by procedural and mechanical dependency to achieve discursive synergy and interactional sovereignty.

Quantitatively, this shift was evidenced by a nearly three-fold increase in DLI, rising from 0.37 (T1) to 1.02 (T3), and a four-fold surge in MTE, which peaked at 13.11. Ultimately, the multi-phase intervention facilitated a role transformation where learners moved beyond fragmented, dependent participation to achieve complex conversational architectures. These results reinforce the notion that interactional competence in the digital age is an emergent property of the human-AI partnership, stabilized through sustained and strategically design engagement.

The empirical validation of this seven-week developmental model offers several pedagogical implications for the systematic integration of GenAI in EFL curricula. Central to this approach is the implementation of a dual-stage priming-to-interaction workflow, which transitions learners from pre-communicative lexical and meta-discursive priming to spontaneous AI-mediated dialogue. By providing students with structured materials that emphasize not only thematic vocabulary but also procedural instructions such as specific prompts to regulate the AI's speaking pace or output complexity, instructors can lower the initial cognitive load and effectively mitigate the agentic friction that characterizes early human-AI encounters.

Furthermore, these findings necessitate a reconfiguration of the teacher's role within the digital learning environment. Rather than serving as the primary source of linguistic input, the instructor facilitates a dual-stage priming-to-interaction workflow designed to mitigate initial agentic friction characterized by interactional dependency and high frequencies of other-initiated repair and procedural instructions. This shift creates a decentralized, non-judgmental safe space where students can exhaust mechanical struggles and internalize interactional routines without the pressure of human evaluation. By prioritizing the strategic use of digital affordances, educators need to guide learners through a strategic calibration and attain interactional sovereignty as evidenced by a surge in topic durability.

However, the findings also open several avenues for future inquiry. First, while the current study focused on the 7-week duration, further longitudinal research is warranted to assess the long-term stability of these interactional gains. Second, future investigations should explore the intersection of interactional agency with internal psychological constructs, such as speaking anxiety and self-efficacy, to provide a more holistic understanding of the learner's experience. Finally, as AI platforms evolve to include more seamless multimodal affordances, subsequent research should examine how different AI agentic personalities or feedback styles influence the rate of the learner's taming the machine's process.

REFERENCES

Ahearn, L. M. (2001). Language and agency. *Annual Review of Anthropology, 30*(1), 109-137. https://doi.org/10.1146/annurev.anthro.30.1.109

Chen, Y., Ke, N., Huan, L., & Luo, R. (2025). The role of GenAI in EFL speaking: Effects on oral proficiency, anxiety and risk-taking. *RELC Journal*. https://doi.org/10.1177/00336882251341072

Cheon, S. M. (2023). Educational application of ChatGPT: Its impact on Korean university students' English speaking skills. *The Journal of Linguistic Science*, 107, 469–496. https://doi.org/10.21296/jls.2023.12.107.467

Choi, M. G., & Oh, S.-Y. (2026). Developing L2 turn-taking with ChatGPT: A longitudinal conversation analytic study. *System, 138,* Article 103959. https://doi.org/10.1016/j.system.2025.103959

Duff, P. A. (2012). Identity, agency, and second language L2 literary development. In J. P. Gee & M. Handford (Eds.), *The Routledge handbook of discourse analysis* (pp. 410-426). Routledge.

Gao, X. (2010). *Strategic language learning: The roles of agency and context*. Multilingual Matters.

Hall, J. K. (1993). The role of oral practices in the accomplishment of our everyday lives: the case of those who have been there. *Applied Linguistics, 14*(2), 145-166. https://doi.org/10.1093/applin/14.2.145

Hall, J. K. (1995). (Re)creating our worlds with words: A sociohistorical perspective of face-to-face interaction. *Applied Linguistics, 16*(2), 206-232. https://doi.org/10.1093/applin/16.2.206

Im, M., Yoon, T., & Lee, S. (2024). A study on the affective domains and perceptions of college English learners on ChatGPT-based English speaking activities. *Studies in Linguistics, 70,* 267-288. https://doi.org/10.17002/sil..70.20241.267

Ji, H., Han, L., & Park, S. (2024). Teaching foreign language with conversational AI: Teacher-student-AI interaction. *Language Learning & Technology, 28*(2), 91-108. https://hdl.handle.net/10125/73573

Koo, T. K., & Li, M. Y. (2016). A guideline of selecting and reporting intrassclass correlation coefficients for reliability research. *Journal of Chiropractic Medicine, 15*(2), 155-163. https://doi.org/10.1016/j.jcm.2016.02.012

Kramsch, C. (1986). From language proficiency to interactional competence. *Modern Language Journal, 70*(4), 366-372. https://doi.org/10.1111/j.1540-4781.1986.yb05291.x

Lantolf, J. P., & Thorne, S. L. (2006). *Sociocultural theory and the genesis of second language development.* Oxford University Press.

Lee, S.-R., & Pyo, K.-H. (2026). Effects of GenAI-based job interview practice on EFL college students' performance and affective domains. *Studies in Linguistics, 78,* 355-384. https://doi.org/10.17002/si..78.202601.355

Mercer, S. (2011). Understanding learner agency as a complex dynamic system. *System, 39*(4), 427-436. https://doi.org/10.1016/j.system.2011.08.001

Park, E.-J. (2024). A meta-analysis on the comparative effects of AI chatbot utilization in English education programs. *English Language & Literature Teaching, 30*(1), 41-61. https://doi.org/10.35828/etak.2024.30.1.41

Pyo, K.-H. (2026a). A multi-phase developmental analysis of EFL university students' complexity, accuracy, and fluency through ChatGPT-mediated speaking tasks. *ESP Review, 8*(1), 51-66. https://doi.org/10.23191/espkor.2026.8.1.51

Pyo, K.-H. (2026b). Tracking the evolution of EFL college learners' international competence in AI-mediated discourse: A multi-stage analysis. *Journal of the Korean English Education Society, 25*(2), 31-51. https://doi.org/10.18649/jkees.2026.25.2.31.

Pyo, K.-H. (2026c). A multi-phase developmental study of EFL university students' prompt engineering strategies in AI-mediated speaking tasks. *The International Journal of Internet, Broadcasting, and Communication, 18*(2). 412-419. https://doi.org/10.7236/IJIBC.2026.18.3.412

Rha, K.-H. (2024). Exploring exploitability of ChatGPT as a learning platform for EFL college students' speaking. *Studies in Linguistics, 72*, 199-223. https://doi.org/10.17002/sil..72.202407.199

Rha, K.-H., & Baek, J. (2025). Examining changes in Korean college students' perceptions toward ChatGPT use in their English class. *The International Journal of Internet, Broadcasting, and Communication, 17*(1), 346-351. https://doi.org/10.7236/IJIBC.2025.17.1.346

Thorne, S. L., Hellermann, J., & Jakonen, T. (2021). Rewilding language education: Emergent assemblies and rhizomatic learning. In J. P. Lantolf, M. E. Poehner, & M. Swain (Eds.), *The Routledge handbook of sociocultural theory and second language development* (pp. 463-477). Routledge.

Toohey, K. (2019). The onto-epistemologies of new materialism: Implications for applied linguistics pedagogies and research. *Applied Linguistics, 40*(6), 937-956. https://doi.org/10.1093/applin/amy046

Tuncer, S., Licoppe, C., Luff, P., & Heath, C. (2024). Recipient design in human-robot interaction: The emergent assessment of a robot's competence. *AI & Society, 39*(4), 1795-1810. https://doi.org/10.1007/s00146-022-01608-7

van Lier, L. (2008). Agency in the language community. In J. P. Lantolf & M. E. Poehner (Eds.), *Sociocultural theory and the teaching of second language* (pp. 163-186). Equinox.

Vygotsky, L. S. (1978). *Mind in society: The development of higher psychological processes*. Harvard University Press.

Young, R. F. (2011). Interactional competence in language learning and teaching. In E. Hinkel (Ed.), *Handbook of research in second language teaching and learning* (Vol. 2, pp. 426-443). Routledge.

APPENDIX

Sample Worksheet for Speaking Task, Using ChatGPT

* Topic 4: Coping with Exam Stress

I. Preparation for Speaking

1. [Listen 1] 8 Useful Coping Strategies

①	②
③	④
⑤	⑥
⑦	⑧

2. [Listen 2] Fill in the blanks.

1) Before the exam, she _____.

2) After the exam, she _____.

3. Complete the sentences with your own ideas.

1) Before I take a difficult exam, I _____.

2) When I don't know the answer to an exam question, _____.

3) After I finish exams, I _____.

4) When I get my exam results, _____.

II. Speaking Practice with ChatGPT (At least for 15 minutes)

1-1. Write down 2 ways to deal with your exam stress.

① _____ ② _____

1-2. Work with AI to talk about how to deal with exam stress.
Say, "I have 2 effective ways of dealing with my exam stress during the exam week. I want to tell you the two ways in great depth. Could you ask me about them one by one? Wait for my response until I finish. And if there's a critical error in grammar, try to correct me. OK?"

2-1. Work with AI to ask for some suggestions for releasing exam stress before/during/after exam?
Say, "I believe you have great ideas for me to use in order to release exam stress. Right? Could you please share some ideas in three different phases before exam, during exam, and after exam? I would really appreciate if you tell two specific ideas for each phase so that I can practice during my school years."

2-2. After talking with AI, summarize its suggestions by filling in the table below.

1. Before	①
	②
2. During	①
	②

Examples in: English
Applicable Languages: English
Applicable Levels: Tertiary

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