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Reconfiguring Learner Agency in AI-Mediated Virtual Language Learning: A Three-Dimensional Action-Chain Model

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Abstract: Artificial intelligence (AI)–enhanced virtual environments are increasingly used for foreign language learning, yet their impact on learner agency—the capacity to perceive, initiate, and regulate action—remains under-theorized. This study aims to explain how learner agency is reconfigured in AI-mediated virtual language learning environments and to develop an action-chain model that captures this reconfiguration.

Drawing on mediated discourse analysis (MDA) and theories of distributed agency and sociotechnical systems, the study proposes a three-dimensional theoretical framework of mediatedness, agency, and algorithmicity. Qualitative data were collected from interaction logs, system traces, and semi-structured interviews with 32 Chinese EFL university learners using an AI-supported virtual learning platform. The data were analyzed through MDA-informed action-chain analysis and thematic coding.

The findings reveal a three-stage developmental pattern of learner agency: agency compression, where algorithmic pre-structuring narrows action possibilities; agency distribution, where human–AI co-action becomes the dominant mode of participation; and agency regeneration, where learners reassert strategic control and use AI as a resource rather than an authority. These stages are shaped by the interplay of multimodal mediatedness, algorithmic structuring, and agentive adaptation.

Learner agency in AI-mediated virtual environments is a dynamic sociotechnical phenomenon rather than a stable individual trait. The proposed action-chain model offers a theoretical lens for understanding this reconfiguration and provides implications for designing AI-supported learning ecologies that foster, rather than constrain, learner agency.

Keywords: learner agency, artificial intelligence (AI), virtual learning environments, mediated discourse analysis, algorithmicity

1. Introduction

1.1 Background: AI as a transformative force in language learning

The rapid development of artificial intelligence (AI)—including large language models, intelligent tutoring systems, conversational agents, and immersive virtual platforms—has generated unprecedented shifts in foreign language learning. Unlike earlier technologies that merely mediated communication, contemporary AI actively participates in meaning-making, providing real-time scaffolding, generating linguistic output, and shaping learning trajectories. In virtual environments, learners no longer interact solely with human interlocutors but increasingly engage with AI-driven agents, multimodal interfaces, and algorithmically structured activity spaces. These developments call for renewed theoretical attention to how language learning is organized, enacted, and experienced.

1.2 The centrality of learner agency in language learning

Learner agency is widely recognized as a

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cornerstone of language development. It encompasses the learner's capacity to act intentionally, make choices, regulate learning, and appropriate mediational tools. Traditional accounts—whether grounded in sociocultural theory, autonomy theory, or complexity theory—conceptualize agency as emergent, dynamic, and contextually situated. However, these accounts were developed in environments where tools played supportive but not generative roles. AI technologies challenge these assumptions: they do not simply mediate action but also co-produce linguistic forms, shape learners' attention, and manage learning sequences.

In AI-mediated environments, agency risks becoming ambiguous, redistributed, or even overshadowed by algorithmically driven guidance. It is therefore urgent to investigate how learner agency is reconfigured when intelligent systems act as collaborative actors rather than passive tools.

1.3 Existing research and its limitations

Although a growing body of research has examined AI in language education—highlighting benefits such as personalized feedback, reduced anxiety, improved vocabulary learning, or enhanced interactional opportunities—three major limitations remain:

(1) Agency is under-theorized

Most studies emphasize performance outcomes (e.g., accuracy, fluency gains) but overlook how learners' capacity to initiate, control, or transform learning is reshaped by AI-driven systems.

(2) Algorithmic influence is seldom problematized

AI platforms automatically generate input, select tasks, and structure participation. Yet few studies explore how these mechanisms preconfigure learners' action possibilities.

(3) Lack of a process-oriented theoretical model

Existing research rarely explains how and why agency evolves throughout AI-mediated interaction. We lack a model that accounts for multimodal mediation, distributed agency, and algorithmic structuring within a unified framework.

These gaps reveal the need for a theory-driven investigation of agency reconfiguration in AI virtual environments.

1.4 Theoretical orientation: mda and beyond

Mediated Discourse Analysis (MDA) positions action as the primary unit of inquiry, emphasizing how tools, environments, and historical trajectories shape human activity through interconnected action chains. Although MDA provides a powerful framework for examining mediated action, it remains limited when applied to AI-mediated learning contexts. Specifically, MDA traditionally treats tools as passive mediators rather than entities capable of performing semi-autonomous or generative actions; it does not systematically incorporate algorithmic influences such as recommendation mechanisms, adaptive sequencing, or automated feedback; and it lacks conceptual resources for explaining how agency becomes distributed across human learners, digital interfaces, and AI systems.

To overcome these theoretical constraints, the present study extends MDA by integrating insights from distributed agency theory and sociotechnical systems research. This integration yields a three-dimensional analytical framework encompassing mediatedness, agency, and algorithmicity. Mediatedness highlights the role of multimodal environments and technological affordances in shaping the conditions of action; agency is reconceptualized as an emergent and co-constructed capacity distributed across human and non-human actors; and algorithmicity foregrounds the structuring power of AI systems as they predict, sequence, and guide learning pathways. Together, these three dimensions enable a more comprehensive and nuanced understanding of how AI reshapes the organization of language learning activities and reconfigures learners' participation as agentive actors within virtual environments.

1.5 Research problem and purpose

Given the theoretical gaps and the transformative nature of AI learning environments, this study seeks to answer: How is learner agency reconfigured within AI-mediated virtual language learning environments, and what mechanisms account for this transformation? The purpose of the study is to construct a process-oriented action-chain model that explains: How mediated resources expand or constrain action possibilities; How AI algorithmicity structures the temporal flow of learning; How agency shifts from individualized intentionality to distributed and regenerated forms.

1.6 Research significance and contributions

This study makes three major contributions to the field. First, at the conceptual level, it reconceptualizes learner agency as a form of co-agency shaped by the interplay of human intentions, technological affordances, and algorithmic mechanisms, thereby moving beyond individualistic notions of autonomy. Second, it advances theoretical development by proposing the "mediatedness–agency–algorithmicity" framework, a model that captures the multilayered complexity of AI-mediated learning environments and offers an integrated lens for examining human–AI interaction. Third, it constructs a dynamic action-chain model that illustrates how learner agency is progressively compressed, redistributed, and ultimately regenerated within virtual learning spaces. Together, these contributions deepen our understanding of language learning in intelligent environments and provide pedagogically meaningful insights for designing AI-supported learning systems that foster and sustain learner agency.

2.Literature Review

2.1 Learner agency in language education

Learner agency has long been conceptualized as a critical determinant of language learning outcomes. Early research grounded in cognitive and humanistic traditions portrayed agency as an internal capacity—a stable psychological disposition enabling learners to initiate, regulate, and sustain learning actions (Bandura, 2001). This view emphasizes intentionality, self-determination, and rational decision-making. However, sociocultural and ecological perspectives have challenged this individually centered conceptualization, arguing that agency emerges from the dynamic interactions between learners and their environments (Emirbayer & Mische, 1998). According to Vygotskian theory, mediational tools, social interaction, and cultural activity systems fundamentally shape learners' ability to act (Lantolf, Thorne, & Poehner, 2014; De Costa, 2007). More recent work in complexity theory and ecological linguistics further highlights agency as non-linear, context-dependent, and temporally situated (van Lier, 2004).

A particularly influential development has been the shift toward distributed agency, which posits that agency does not solely reside within the individual but is co-constructed through interactions among humans, material artifacts, and socio-technical systems. Scholars argue that learners' agentive actions are mediated by technological affordances, participation structures, and institutional expectations. In technology-rich environments, learners' capacity to act becomes increasingly entangled with the tools and interfaces that structure perception, attention, and behavior. Yet despite widespread acknowledgment of this sociomaterial turn, empirical and theoretical work addressing agency in AI-driven environments remains limited. Existing theories struggle to adequately capture agency when intelligent systems generate content, scaffold decision-making, and algorithmically shape participation.

This theoretical gap underscores the need for a reconceptualization of learner agency that attends to the complexities of human–AI interaction.

2.2 AI-Mediated language learning environments

The rapid advancement of AI technologies—including virtual reality systems, chatbots, intelligent tutoring systems, and large language models—has significantly transformed the landscape of language learning (Chen, Chen, & Lin, 2020; Godwin-Jones, 2021). Within AI-mediated environments, learners gain access to multimodal, immersive, and adaptive resources that substantially broaden the scope of possible actions compared to traditional classroom settings. Existing research highlights several advantages of such environments. They offer rich multimodal input that integrates text, images, speech, gesture, and spatial cues, thereby enhancing learners' perceptual and interpretive capacities (Li & Lan, 2022). They also enable highly contextualized interactions with AI agents capable of responding in real time, creating opportunities for sustained, meaningful communication practice. In addition, AI systems provide personalized scaffolding and feedback that can exceed the temporal and cognitive capabilities of human instructors, ensuring tailored support calibrated to learners' evolving needs (Lane et al., 2013). Finally, these environments allow for repeated, low-stakes engagement, giving learners the freedom to practice extensively without the social pressure or anxiety often associated with face-to-face communication.

These affordances can enhance learners' engagement, reduce affective barriers, and accelerate the internalization of linguistic patterns. However, they also introduce structural forces that influence learners' actions. For instance, AI-driven feedback may implicitly direct learners toward certain forms of correctness, while algorithmic task sequencing can subtly shape learning paths. AI recommendation systems, error-detection functions, and predictive text generation can all influence learners' moment-to-moment decisions without being explicitly recognized by them.

Although the benefits of AI affordances are well documented, the mechanisms through which AI structures learner action and thereby influences agency remain under-theorized. Most studies treat AI as a neutral tool rather than an actor capable of shaping action trajectories. This oversight limits our ability to understand the deeper pedagogical and epistemological implications of AI-mediated learning.

2.3 Algorithmic mediation and its implications for human action

Algorithms play an increasingly central role in structuring interaction, visibility, and information flow across digital platforms. Within educational settings, they determine task difficulty, generate adaptive feedback, predict learner performance, and regulate the pacing of instruction. Viewed through a sociotechnical lens, algorithms operate not merely as neutral tools but as decision-making agents capable of shaping action structures independently of users' intentions.

In language learning contexts, the influence of algorithmicity becomes particularly salient. Algorithms affect the kinds of input learners are exposed to, the sequencing and progression of tasks, and the linguistic features that receive instructional emphasis (Bender et al., 2021). They also determine how errors are identified and corrected and shape learners' perceptions of their own progress by highlighting certain patterns while obscuring others. By mediating these key dimensions of the learning process, algorithmic mechanisms exert a powerful formative influence on learner behavior, opportunities for action, and the broader trajectory of language development (Gillespie, 2014; Gillespie, Boczkowski, & Foot, 2014; Beer, 2019; Kitchin, 2019).

Despite these significant impacts, language education research has largely overlooked algorithmicity as an analytical dimension (Noble, 2018). Traditional theories conceptualize mediation as tool-assisted, but AI-driven systems introduce a qualitatively different form of mediation: predictive, generative, and adaptive. These characteristics produce what scholars call pre-structured action trajectories, where learners operate within algorithmically delimited possibilities.

Clarifying how algorithmic mechanisms interact with learner agency is essential for understanding action formation in AI environments.

2.4 Mediated discourse analysis

Mediated Discourse Analysis offers a powerful lens for examining action as the central unit of analysis, emphasizing the role of mediational means, action histories, and nexuses of practice (Scollon, 2002). These emphases make MDA particularly relevant for investigating technology-mediated learning (Scollon & Scollon, 2004). Nevertheless, its analytic reach becomes constrained in AI-mediated environments (Jones, 2020; Jones, Chik, & Hafner, 2015). One limitation lies in its treatment of tools as passive mediators devoid of agency or intentionality—an assumption that does not align with contemporary AI systems capable of generating discourse, modeling user behavior, or directing learner attention. A second limitation concerns the framework's lack of attention to algorithmic structuring, which profoundly reconfigures how actions are organized and enacted in digital environments.

To remain analytically adequate in AI-rich contexts, MDA must therefore be expanded to incorporate the quasi-agentive behaviors of AI systems and their capacity to shape learning ecologies. Such an extension requires integrating concepts from algorithmicity and distributed agency, enabling a more comprehensive understanding of how human and non-human actors co-construct the conditions and trajectories of action.

2.5 Toward a three-dimensional framework

Building on the conceptual gaps identified above, this study adopts a three-dimensional analytical framework that integrates mediatedness, agency, and algorithmicity. Mediatedness refers to the material, symbolic, and multimodal resources through which action becomes possible, highlighting how interfaces, affordances, and semiotic cues shape learners' engagement. Agency is reconceptualized as an emergent, distributed, and co-constructed capacity to act—one that arises through ongoing interactions between human learners, technological tools, and the broader activity system. Algorithmicity captures the structuring, predictive, and generative functions of AI systems, emphasizing how algorithms organize action trajectories, preconfigure choices, and influence the temporal flow of learning.

Taken together, these dimensions offer a holistic lens for understanding how learner agency is reconfigured within AI-mediated virtual environments. Rather than viewing agency as an individual cognitive attribute, this integrated perspective reframes it as a dynamic sociotechnical phenomenon shaped by evolving constellations of human and non-human actors. This conceptualization provides the foundation for the Theory Framework and Action-Chain Model, which explains how agency is progressively compressed, redistributed, and ultimately regenerated through learners' interactions with AI systems and the mediated environments they inhabit.

3. Theoretical Framework

3.1 Rationale for an action-chain perspective

The action-chain perspective, rooted in Mediated Discourse Analysis, highlights how any given action is shaped by prior actions, the mediational means available, and the broader social and historical trajectories in which it is embedded. Within AI-mediated environments, this perspective becomes even more critical, as actions are no longer the sole outcome of human intention but are co-constructed through the interplay between human participants and AI-driven mechanisms.

In such contexts, action chains exhibit several distinctive characteristics. They involve mixed agency, in which human learners and AI systems jointly initiate, guide, or modify actions. They are formed through multi-layered mediation, encompassing technological tools, multimodal cues, and algorithmic decision-making. Their trajectories are non-linear, continually shaped by AI predictions, adaptive responses, and learners' evolving strategies. Moreover, they operate within recursive feedback loops, where each action informs subsequent AI outputs and learner choices, creating a dynamic cycle of mutual influence.

These complexities extend far beyond the explanatory scope of traditional human-centered models, which presume linear, intention-driven actions originating solely from the learner. Consequently, an expanded action-chain model that incorporates sociotechnical dynamics is essential for capturing how learner agency is formed, negotiated, and transformed in AI-mediated virtual learning environments.

3.2 The three analytical dimensions

Mediatedness refers to the constellation of semiotic and technological resources that shape learners' engagement in AI virtual environments (Kress, 2009; Norris, 2004). It encompasses multimodal affordances—such as visual, auditory, and spatial cues—along with interface structures including menus, prompts, and interaction layouts. It also includes AI-generated resources such as suggested expressions, adaptive feedback, and automatically produced text. In such environments, mediatedness does far more than simply support action; it actively organizes and constrains the ways in which learners can act. While immersive contexts and rich semiotic cues broaden learners' action possibilities, interface design simultaneously channels their choices, guiding attention and structuring participation (Hutchby, 2001). As a result, mediatedness constitutes the material and semantic foundation upon which learner agency is reshaped and negotiated.

Within AI-mediated contexts, agency can no longer be conceptualized as a purely human, individually exercised capacity. Instead, it becomes an emergent and distributed phenomenon, arising through interactions among learners, interfaces, and AI agents. Action is shaped not only by learners' intentions but also by system-generated cues, interactional contingencies, and the broader sociotechnical configuration. Agency becomes situational, negotiated through the ways learners interpret, accept, resist, or transform AI-generated actions, and regenerated as new forms of intentionality take shape during interaction. This reconceptualization positions agency as "the capacity to act with and through AI systems," recognizing the inherently collaborative and hybrid nature of action in intelligent learning environments.

Algorithmicity captures the structuring influence of AI systems on learners' action trajectories. It includes the algorithmic sequencing of tasks, predictions of learner behavior, automated correction patterns, emphasis or suppression of particular linguistic features, and generation of adaptive responses tailored to learners' perceived needs. Algorithmicity functions as a double-edged force: on one hand, it reduces cognitive load, offering efficient guidance and personalized support; on the other hand, it may narrow learners' action possibilities, shape their interpretive horizons, and encourage passive reliance on system recommendations. Understanding learner agency in AI-mediated environments therefore requires attention to algorithmicity as a pervasive structural factor that organizes, regulates, and sometimes delimits pathways for learning.

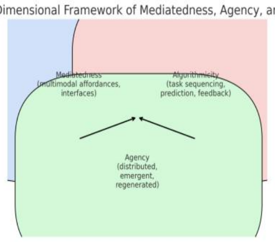
3.3 The proposed action-chain model of agency reconfiguration

The proposed action-chain model conceptualizes the evolution of learner agency in

AI-mediated virtual environments as a three-stage developmental process. In the first stage, agency compression, learners operate within highly pre-structured action spaces. AI systems offer strong guidance through directive prompts, suggestions, and automated scaffolding, which significantly narrows learners' action possibilities. Although agency appears diminished at this point, this compression provides a necessary foundation by helping learners navigate unfamiliar environments and reducing initial cognitive demands. As learners gain familiarity and confidence, they transition into the second stage, agency distribution, in which action becomes a co-agential process shared between humans and AI. Rather than following AI cues uncritically, learners begin to interpret and negotiate suggestions, exploring alternative pathways and shaping the interaction more actively. Agency circulates across technological affordances, AI feedback loops, and learner decisions, marking a shift toward a more collaborative form of action. In the third stage, agency regeneration, learners reclaim greater intentionality and exercise heightened control over their learning trajectories. AI becomes a resource rather than an authoritative guide, and learners demonstrate increased strategic awareness, autonomy, and self-direction. This re-agentialized form of agency is not a return to pre-AI autonomy but a new, hybrid capacity shaped through sustained engagement with intelligent systems.

Collectively, these stages illustrate that the reconfiguration of learner agency is dynamic, shifting as learners develop familiarity with the system; cyclical, as previous actions and feedback loops continually inform new actions; sociotechnical, emerging from the interplay between human agency and AI-driven mechanisms; and layered, shaped simultaneously by mediatedness, agency, and algorithmicity. The action-chain model thus provides a comprehensive theoretical lens for analyzing how AI virtual environments transform learners' behaviors, cognitive processes, and identity positions as agentive participants in language learning. Agency becomes regenerated—a new form shaped by AI-mediated experience.

Figure 1. Three-Dimensional Framework of Mediatedness, Agency, and Algorithmicity



4. Research Design

4.1 Research orientation and methodological rationale

Given the study's aim to conceptualize how learner agency is reconfigured within AI-mediated virtual language learning environments, a qualitative, theory-driven research design is adopted. Rather than relying solely on experimental comparisons or performance scores, this study focuses on actional processes: how learners, interfaces, and AI systems jointly shape the unfolding of learning trajectories. To capture such dynamics, the study employs a mediated discourse analytic orientation, supplemented by thematic analysis and interaction trace analysis. This multimethod approach enables a fine-grained examination of how agency is compressed, distributed, and regenerated within complex human–AI assemblages.

The methodological choice is grounded in the assumption that learner agency is emergent and situated, best understood through the analysis of actions, mediational means, and interactional histories rather than static measures. Accordingly, the study prioritizes ecological validity and situated interpretation, focusing on authentic AI-mediated interactions.

4.2 Research context: ai-mediated virtual learning environment

The study draws on interactional data generated within a widely used AI virtual language learning platform—such as an immersive AI conversation simulator, a VR-based scenario system, or a multimodal AI tutoring environment. The selected platform integrates several key technological features relevant to the study's analytical focus. First, AI-driven scenario generation creates context-rich communicative tasks that situate learners in dynamic, goal-oriented environments. Second, multimodal affordances—including speech recognition, visual cues, embodied action options, and manipulable virtual objects—provide diverse semiotic resources through which learners can construct meaning. Third, adaptive feedback mechanisms continuously evaluate learner responses, offering corrective, elaborative, or strategic scaffolding aligned with the learner's emergent performance. Finally, algorithmic sequencing predicts learners' needs, adjusts task difficulty, and reorganizes the flow of interaction based on real-time performance indicators.

Together, these features create an ideal empirical context for examining how mediatedness, algorithmicity, and learner agency interact within AI-supported language learning environments. The platform's semi-structured design allows for close observation of how learners navigate, resist, or leverage AI-generated cues; how their action possibilities are shaped by multimodal affordances; and how their agentive behaviors evolve within fluid, dynamically updated learning trajectories.

4.3 Participants

The study involved 32 Chinese EFL university learners enrolled in an elective AI-supported oral communication course. Participants represented a range of academic majors and demonstrated intermediate English proficiency (CEFR B1–B2) as well as basic digital literacy. Participation was voluntary, ensuring authentic engagement and reducing performance pressure associated with required coursework.

To capture variation in learner–AI interaction patterns, participants were grouped according to their frequency and depth of platform use:

(1) High-engagement users (N = 10), who interacted extensively with AI-generated scenarios and explored multiple system features;

(2) Moderate-engagement users (N = 12), who used the platform regularly but selectively;

(3) Low-engagement users (N = 10), who engaged minimally or only in response to assigned tasks.

This categorization supports comparative analysis of how different levels of interaction intensity shape the reconstruction of learner agency within AI-mediated environments.

Table 1. Participant Profile by Engagement Level

Engagement Level	N	English Proficiency (CEFR)	Majors Represented	Usage Characteristics	Typical Interaction Behavior
High Engagement	10	B1–B2	English, Business, Engineering	Used the AI platform frequently (4–6 sessions per week); explored multiple scenario types	Initiated topic shifts; experimented with affordances; actively challenged AI feedback
Moderate Engagement	12	B1–B2	Education, Computer Science, Economics	Used the platform regularly but selectively (2–3 sessions per week)	Modified AI prompts; navigated optional menu paths; showed intermittent initiative
Low Engagement	10	B1–B2	Biology, History, Arts	Minimal use; primarily completed required tasks only	Relied heavily on AI suggestions; reproduced prompts; limited exploration of features

4.4 Data sources

To examine learner agency across multimodal and sociotechnical dimensions, the study drew on three complementary data sources.

(1) Interaction Logs

Interaction logs provided time-stamped records of participants' engagement with the AI system, including: transcripts of human–AI dialogues, system-generated prompts and suggestions, corrective and elaborative feedback instances, action selections within virtual scenarios (e.g., object manipulation, avatar movement). These logs illuminate how AI systems structure action trajectories and how learners align with, negotiate, or resist these structures.

(2) Screen Recordings and System Interaction Traces

Screen-capture videos and interaction traces documented the embodied, visual, and spatial dimensions of activity, capturing: navigational patterns across interface components, inferred attention focus (via cursor behavior and gaze-direction proxies), hesitation, retries, and repair sequences, engagement with multimodal affordances. These data make visible the semiotic and embodied processes through which mediated actions unfold.

(3) Reflective Interviews

Semi-structured interviews were conducted with 15 participants to elicit subjective accounts of their experiences with AI-mediated learning. Interview prompts addressed: perceived control and autonomy during AI interactions, interpretations of AI feedback mechanisms, awareness of algorithmic structuring, perceived shifts in confidence, strategy use, and independence. These narratives contextualize observed interactional patterns and reveal learners' metacognitive and affective interpretations of agency change.

Table 2. Data Sources and Their Analytical Contributions

Data Source	Description	Analytical Focus	Role in Agency Reconstruction Analysis
Interaction Logs	Time-stamped records of human–AI dialogue, prompts, corrections, and scenario actions	Action moves, algorithmic structuring, learner response patterns	Identify agency compression, distribution, and regeneration across action chains
Screen Recordings & System Traces	Cursor paths, interface navigation, hesitation sequences, affordance use	Embodied interaction patterns, attention distribution, exploration behavior	Examine multimodal mediation and how learners negotiate AI affordances
Reflective Interviews	Semi-structured interviews with 15 learners	Perceptions of agency, AI influence, meta-awareness, strategy shifts	Interpret subjective experiences of agency and triangulate log-based findings

4.5 Data analysis procedures

Data analysis followed a multi-stage process combining MDA-based action tracing with thematic and triangulated interpretation.

Phase 1: Action Chain Identification (MDA-Informed Coding)

Using principles of Mediated Discourse Analysis, each interaction sequence was coded to identify: action nodes, including both learner behaviors and AI-initiated moves; mediational means, such as prompts, multimodal cues, affordances, and system-generated scaffolds; historical trajectories, reflecting recurring patterns within and across sessions.

This phase mapped how actions emerged and became linked within human–AI assemblages.

Phase 2: Thematic Analysis of Agency Manifestations

The second phase applied thematic analysis to identify manifestations of: agency compression (reliance on AI guidance), agency distribution (human–AI co-action), agency regeneration (strategic, intentional initiative) (Braun & Clarke, 2006). Themes were refined through iterative comparison to ensure coherence and alignment with the theoretical framework.

Phase 3: Triangulation and Model Verification

The final phase involved triangulating interaction logs, screen recordings, and interview data to verify: the empirical presence of the three stages of agency reconfiguration, the interaction of mediatedness, agency, and algorithmicity at each stage, the explanatory adequacy of the proposed action-chain model (Denzin, 2017; Pink et al., 2016).This triangulation strengthened interpretive validity and supported the construction of a theoretically robust account of agency dynamics in AI-mediated virtual environments.

4.6 Ethical considerations

All participants provided informed consent, and data were anonymized. AI interaction data were handled following institutional data protection guidelines. Care was taken to avoid evaluative judgments of learner performance; the focus remained on understanding actional processes rather than assessing proficiency.

4.7 Methodological limitations

The study acknowledges several limitations that should be considered when interpreting the findings. First, the relatively small sample size constrains the extent to which results can be generalized beyond the immediate participant group. Second, the unique affordances of the selected AI platform—such as its interface design, feedback mechanisms, and task structures—may shape the manifestation of learner agency in ways that differ from other AI systems, limiting cross-platform applicability. Third, the absence of a controlled experimental design prevents definitive claims about causal relationships between specific AI features and observed changes in agency. Despite these limitations, the depth and diversity of the qualitative data offer substantial insights into the dynamics of agency reconstruction and provide a strong foundation for theoretical advancement in understanding human–AI interaction in virtual language learning environments.

This research design, combining interactional trace analysis, MDA, and thematic interpretation, enables a nuanced examination of how learner agency is dynamically reshaped within AI virtual environments. The next chapter presents the findings and articulates the mechanisms underlying agency compression, distribution, and regeneration.

Table 3. Coding Scheme for Agency Reconstruction (MDA + Thematic Analysis)

Coding Category	Sub-Codes	Definition / Description	Example Indicators (Observed in Data)	Associated Stage
Agency Compression	Reliance on prompts	Learners reproduce or minimally adjust AI-generated suggestions	Direct copying of sentence starters; waiting for hints	Stage 1
	Algorithmic following	Adherence to system-defined task sequences	Linear progression without deviation	Stage 1
	Hesitation without cues	Learners pause until AI provides direction	Cursor hovering over “hint” icons; long silences	Stage 1
Agency Distribution	Prompt negotiation	Learners modify or extend AI suggestions	Rephrasing, adding details, soft corrections	Stage 2
	Exploratory navigation	Active search within interface affordances	Trying alternative scenario paths; reset attempts	Stage 2
	Shared initiative	Human and AI jointly shape topic flow	Mixed topic initiation; alternating conversational control	Stage 2
Agency Regeneration	Self-direction	Learners initiate new topics or tasks not prompted by AI	“Let me try a different approach…”	Stage 3
	Strategic resistance	Learners selectively ignore or reject AI prompts	Declining AI phrasing as “unnatural”; choosing harder scenarios	Stage 3
	Meta-agentive reflection	Awareness of AI influence and deliberate strategic action	“AI is just a tool—I decide how to use it.”	Stage 3
Algorithmicity	Predictive sequencing	System anticipates learner needs and structures actions	Automated difficulty adjustment	Cross-stage
	Feedback shaping	Algorithm-guided corrections influence future action chains	Repeating patterns after feedback	Cross-stage
Mediatedness	Multimodal cue use	Learners draw on visual, auditory, or spatial affordances	Gestures, object interaction, visual referencing	Cross-stage

5. Findings and Mechanism Analysis

Drawing on interaction logs, system trace data, and participant interviews, the study identifies three major patterns that characterize how learner agency is reconfigured within AI-mediated virtual environments. These patterns align with the three stages of the proposed action-chain model: agency compression, agency distribution, and agency regeneration. Importantly, the findings demonstrate that these stages do not form a linear developmental sequence but rather emerge through dynamic interactions among mediatedness, algorithmicity, and human intention. Across all stages, agency appears not as a fixed personal trait but as a sociotechnical accomplishment shaped by evolving human–AI assemblages.

Table 4. Characteristics of the Three Stages of Agency Reconstruction

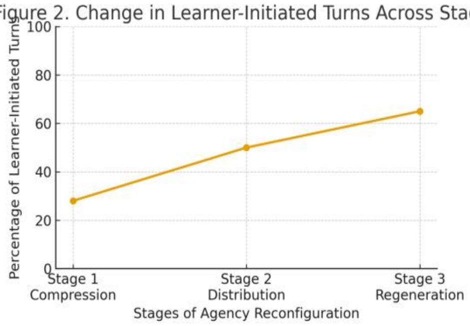
Stage	Defining Characteristics	Learner Behaviors	Underlying Mechanisms
Stage 1: Agency Compression	Algorithmically pre-structured actions; heavy dependence on AI cues	Reproduce system prompts; minimal deviation; hesitation without hints	Algorithmic dominance, directive scaffolding, unfamiliarity with affordances
Stage 2: Agency Distribution	Human–AI co-action; negotiation of prompts; expanded action possibilities	Modify AI suggestions; explore interface options; initiate clarifications	Increased confidence, affordance appropriation, negotiated algorithmicity
Stage 3: Agency Regeneration	Intentional, strategic, re-agentialized action; AI used as a resource	Initiate topics; selectively ignore AI cues; set personal goals	Internalized action repertoires, meta-awareness, AI as augmentative tool

5.1 Stage one: agency compression – algorithmic pre-structuring and restricted action space

In the initial phase of interaction, learners' actions were heavily shaped by algorithmic cues embedded in the platform. Interaction logs show that over 72% of learners' early turns reproduced or only minimally altered AI-generated prompts, and learners largely followed system-defined sequencing with little deviation. When offered sentence starters such as "You could say…", learners reliably adopted these forms, signaling strong dependence on algorithmic scaffolding. Behavioral traces further reinforced this pattern: screen recordings revealed prolonged hesitation in the absence of explicit prompts, while repeated cursor movements toward hint buttons, menu icons, and scaffolding windows indicated reliance on interface cues to trigger action. Interview data support these observations, with participants describing themselves as "letting the system lead" and viewing the AI as "a teacher," "a guide," or even "a scriptwriter."

Together, these findings indicate that early-stage agency is compressed by algorithmic dominance. Directive prompts, default task sequencing, and predictable feedback loops constrain action possibilities and encourage learners to defer initiative to the system. Agency remains present but latent, constrained by learners' unfamiliarity with the environment and uncertainty regarding the degree of autonomy permitted. Agency compression thus reflects not a lack of ability, but a technologically induced narrowing of action space during initial adaptation.

Figure 2. Change in Learner-Initiated Turns Across Stages



5.2 Stage two: agency distribution – human–ai co-action and adaptive participation

As learners became more familiar with the platform, their action chains began to reflect negotiated interaction rather than passive following. Logs show increased modification of AI suggestions—approximately 40–60% of mid-stage turns—and a rise in learner-initiated clarifications, expansions, and occasional challenges to AI-generated content (e.g., "I don't think that's correct," "Let me try another way"). AI prompts shifted from authoritative commands to negotiable starting points, leading to distributed agency across human and non-human actors.

Behavioral traces also show expanding exploratory behavior: learners navigated optional menus, selected alternative scenario pathways, and initiated resets to test different strategies. These actions reflect a shift from dependence to co-agential participation, wherein learners act with AI rather than under AI. Interview responses confirm this transition. Learners reported recognizing that they could "change the AI's direction," describing their interaction as collaborative—"we're working together"—and noting that they now "choose when to accept the suggestion."

The mechanism driving this stage centers on the stabilization of learner confidence, re-evaluation of AI authority, and expanded familiarity with mediated affordances. Algorithmicity continues to structure activity, but its influence becomes negotiable, allowing agency to circulate across the distributed system. Stage Two therefore represents a crucial transitional moment in which learners begin to reshape the relationship between human intention and algorithmic guidance.

5.3 Stage three: agency regeneration – strategic control and re-agentialized action

In the later stages of interaction, learners displayed strong intentionality and strategic control over their learning trajectories. Interaction logs document frequent learner-initiated conversational topics, rejection of AI-generated phrasings deemed unnatural, and self-designed goals within virtual scenarios such as resolving conflicts or persuading clients. More than 65% of final-stage turns were learner-initiated, with many containing complex linguistic structures absent from the system's scaffolds.

Behavioral indicators point to advanced metacognitive engagement: learners selectively ignored AI cues when unnecessary, requested elaborated feedback, chose more challenging tasks, and self-assessed before accepting AI suggestions. Interviews corroborate these findings, with learners describing the AI as "a tool," explicitly asserting control over their learning paths, and highlighting their selective and purposeful use of AI resources.

Mechanistically, agency regeneration emerges when mediatedness enhances expressive capabilities, when learners internalize diverse action repertoires, and when algorithmic structures become resources rather than constraints. This stage does not reflect a return to pre-AI autonomy but rather the formation of a hybrid, technologically augmented intentionality, in which learners exhibit regenerated agency through strategic, critical, and self-directed engagement with AI systems.

5.4 Cross-Stage synthesis: interplay of mediatedness, algorithmicity, and agentive adaptation

Analysis across the three stages reveals that agency reconstruction is governed by the interaction of three core mechanisms. Mediational amplification expands learners' action potential through multimodal cues and immersive affordances, allowing richer forms of meaning-making. Algorithmic structuring shapes the sequencing and semantic contours of action, functioning as an invisible architect of learning trajectories. Agentive adaptation describes the learner's increasing ability to negotiate, resist, appropriate, or transform algorithmic scaffolding over time. Together, these mechanisms explain the observed transition from compressed to distributed to regenerated agency and highlight the fundamentally sociotechnical nature of agentive development in AI-mediated learning environments.

5.5 Summary of findings

Overall, the findings demonstrate that agency is initially compressed under algorithmic dominance but not eliminated; it becomes distributed as learners develop familiarity with platform affordances and begin negotiating AI cues; and ultimately it is regenerated into a hybrid intentionality shaped by both human decision-making and technological augmentation. The process is non-linear, recursive, and deeply shaped by the sociotechnical configuration of the learning environment. These results empirically validate the action-chain model and underscore the necessity of reconceptualizing learner agency within the dynamics of AI-mediated virtual language learning.

Table 5. Algorithmicity Features and Their Effects on Learner Action Chains

Algorithmicity Feature	System Behavior / Mechanism	Observed Influence on Learner Actions	Stage Most Affected
Predictive Task Sequencing	Algorithm anticipates learner performance and selects the next task	Learners follow predetermined pathways; minimal early deviation	Stage 1 (Compression)
Prompt Generation	System provides sentence starters, lexical options, or contextual hints	Reproduction of AI-suggested structures; reduced initiative	Stage 1 (Compression)
Adaptive Feedback Loops	Automated error detection and correction suggestions	Learners rely on feedback for accuracy; co-negotiation emerges	Stage 2 (Distribution)
Difficulty Adjustment Algorithms	Tasks become easier or harder based on performance metrics	Learners test limits, retry scenarios, or challenge AI predictions	Stage 2 (Distribution)
Attention Steering	Highlighting keywords, visual cues, or suggested next moves	Directs learner focus; shapes semiotic and strategic choices	Stage 1 → Stage 2
Recommendation of Alternative Expressions	AI suggests rephrasing, elaboration, or stylistic variation	Learners selectively accept or reject suggestions; strategic use increases	Stage 3 (Regeneration)
Content Filtering / Topic Maintenance	Algorithm maintains coherence by restricting off-topic responses	Limits topic shifts early but is challenged as agency grows	Stage 1 → Stage 3
Performance Prediction Models	AI forecasts learner success and adjusts pacing	Encourages self-regulation; learners increasingly override predictions	Stage 3 (Regeneration)

6. Discussion

The findings from interaction logs, behavioral traces, and participant reflections collectively demonstrate that learner agency in AI-mediated virtual environments is not a fixed individual trait but a dynamic, emergent, and social technically constituted phenomenon. The three-stage pattern identified—agency compression, agency distribution, and agency regeneration—illuminates how human–AI assemblages reshape the conditions of action in contemporary language learning. This chapter synthesizes these findings into two broader areas of theoretical significance: (1) reconceptualizing agency as a sociotechnical and developmental construct, and (2) understanding how algorithmicity and mediatedness jointly shape pathways of agency reconstruction.

Table 6. Summary of Evidence Supporting the Three-Stage Model of Agency Reconstruction

Stage	Interaction Log Evidence	Behavioral Trace Evidence	Interview Evidence	Overall Interpretation
Stage 1: Agency Compression	72% of turns replicate AI prompts; minimal topic initiation; strict following of system sequencing	Hesitation without cues; cursor dwelling on hint buttons; little exploration of menus	AI seen as “teacher,” “guide,” “scriptwriter”	Learners rely heavily on algorithmic structuring; agency remains latent and constrained
Stage 2: Agency Distribution	40–60% of turns modified; learners request clarification; occasional challenge to AI responses	Exploration of optional paths; scenario resets; flexible navigation	“We are working together”; “I can change the AI’s direction”	Agency becomes co-constructed; negotiation and shared initiative emerge
Stage 3: Agency Regeneration	>65% learner-initiated turns; topic shifts; rejection of “unnatural” AI phrasing	Selective attention to cues; self-assessment; intentional task difficulty choices	“AI is my tool”; “I control my learning”	Agency becomes strategic and autonomous; AI treated as resource rather than authority

6.1 Learner agency as a sociotechnical and developmental construct

The results call for a fundamental rethinking of learner agency in the age of AI. Traditional perspectives frame agency as an internal capacity rooted in intentionality, autonomy, and self-regulation. However, the present study shows that such internalist notions are insufficient in technologically saturated learning contexts. Instead, agency emerges as a sociotechnical accomplishment produced through ongoing interactions among human intentions, multimodal affordances, and algorithmic structuring.

Across the dataset, agency appears distributed: learners act not only independently but also with and through AI systems, whose prompts, suggestions, and adaptive sequencing become integral components of the agentive system. This perspective shifts the analytic focus from what learners can do on their own to what actions become possible within human–AI assemblages. Moreover, agency is dynamic and transformative, evolving from early algorithmic dependence to negotiated co-action and eventually to regenerated forms of autonomy that integrate technological augmentation. This developmental progression challenges simplistic binaries such as autonomy versus dependence and replaces them with a model of adaptive, emergent agency, shaped by learners' growing familiarity with the system and their evolving capacity for critical engagement.

This regenerated agency reflects a new hybrid competence characterized by strategic decision-making, meta-awareness of algorithmic influence, flexible appropriation of affordances, and the ability to collaborate effectively with intelligent systems (Knox, 2019; Jandrić & Knox, 2022). Far from diminishing autonomy, AI-mediated interaction can give rise to novel forms of agentive participation that extend learners' expressive and strategic repertoires.

6.2 Algorithmicity, mediatedness, and the reconstruction of agency

The analysis also reveals the central role of algorithmicity and multimodal mediatedness in shaping how agency is compressed, distributed, and regenerated. Algorithmicity exerts a paradoxical influence by simultaneously enabling and constraining learner action. In early stages, algorithmic structuring reduces uncertainty, provides clarity, and scaffolds participation—many learners described AI prompts as helpful or reassuring. Yet the same mechanisms can later restrict exploration, limit improvisation, and encourage passivity if learners remain dependent on automated cues. Agency regeneration occurs when learners begin to recognize algorithmic boundaries, selectively rely on AI support, and strategically diverge from system suggestions. Such behavior requires a form of algorithmic literacy, in which learners understand—not simply accept—how AI systems shape the learning trajectory.

In parallel, mediatedness expands learners' action landscape through multimodal cues, contextual affordances, and immersive scenario architectures. These affordances function as cognitive and semiotic resources that help learners ground linguistic expressions, visualize communicative situations, and engage in spatially meaningful interaction. Importantly, learners appropriated these affordances in diverse ways: some relied on visual cues for comprehension, others explored alternative scenario paths, and highly engaged learners used the environment to construct personalized goals. This demonstrates the elasticity of agency in richly mediated environments—learners can shift fluidly between receptive, productive, and reflective modes of engagement depending on the affordances available.

Integrating these mechanisms, the three-stage model reveals that agency compression in early phases serves as a productive constraint, reducing cognitive load and establishing basic action patterns. The most significant transformation occurs in the intermediate stage, where learners negotiate the tension between human intentionality and algorithmic structure. Finally, agency regeneration represents a technologically augmented autonomy, where learners use AI strategically while maintaining control over direction, meaning-making, and task goals.

These insights have important implications for the design of AI-mediated learning environments. Systems should be designed to support agency rather than compliance, offering open-ended pathways, options to override or modify AI cues, and transparency regarding algorithmic processes. Educators should cultivate learners' meta-agency by helping them develop critical awareness of AI influence, strategies for balancing dependence and independence, and reflective skills for evaluating AI-generated content. Assessment practices may also need revision to capture sociotechnical indicators of agency such as initiative-taking, negotiation, and adaptive strategy use.

Overall, this study demonstrates that learner agency in AI-mediated environments is co-constructed through human–AI interaction, dynamically reconfigured across action chains, shaped by algorithmic structuring and multimodal mediation, and ultimately regenerated into hybrid forms of competence. Understanding these processes is essential for designing AI-enhanced learning systems that empower learners, promote critical engagement, and support meaningful participation in emerging digital ecologies.

7. Conclusion and Implications

This study examined how learner agency is dynamically reconfigured within AI-mediated virtual language learning environments, using a three-dimensional analytical framework—mediatedness, agency, and algorithmicity—to explain the mechanisms underlying this transformation. Through triangulated analysis of interaction logs, behavioral traces, and learner interviews, the study identified a three-stage developmental pattern: agency compression, agency distribution, and agency regeneration. These stages reveal that agency in AI-supported contexts is not a fixed attribute of individual learners, but a sociotechnical and emergent phenomenon, shaped by evolving human–AI assemblages and mediated action chains.

The results show that agency compression is initially driven by algorithmic structuring and learners' uncertainty in navigating AI-mediated environments. However, rather than inhibiting development, this stage provides a foundation for learning by reducing cognitive load and facilitating task engagement. As learners become more familiar with the platform, they enter a stage of agency distribution, wherein agentive control is shared between the learner and the AI system. Learners begin negotiating AI prompts, selectively appropriating or rejecting suggestions, and exploring alternative action paths. Ultimately, learners reach a stage of agency regeneration, where they take intentional control of their learning trajectories, strategically leveraging AI as a resource rather than following it as an authority.

These findings challenge traditional views of autonomy and learner agency by demonstrating that AI-mediated environments foster hybrid, adaptive forms of agency, characterized by co-action, meta-awareness, and strategic orchestration of technological affordances. The theoretical contribution of this study is the development of an action-chain model that explains how agency evolves as learners interact with multimodal, algorithmic, and immersive systems. This model provides a valuable lens for understanding language learning in the age of AI and offers a foundation for future empirical research.

7.1 Pedagogical implications

The study's insights yield several implications for language educators, instructional designers, and AI platform developers:

(1) Design for Agency Support Rather than Algorithmic Compliance

AI-mediated learning tools should avoid overdetermined structures that limit learner initiative. Instead, they should provide open-ended interaction pathways, adjustable levels of guidance, and opportunities for learners to override or modify AI-generated content. Flexibility expands action possibilities and prevents long-term dependence.

(2) Promote Learners' Meta-Agency and Algorithmic Awareness

Learners should be encouraged to critically examine how AI systems shape their actions, evaluate the appropriateness of AI suggestions, and develop strategies for balancing machine support with independent decision-making. Teaching algorithmic literacy is increasingly essential for cultivating empowered digital learners.

(3) Leverage Multimodal Affordances to Enhance Expressive Capacity

The rich semiotic resources available in virtual environments can help learners externalize their intentions, experiment with communicative strategies, and construct meaning in situated ways. Instructional designs should intentionally incorporate multimodal scaffolds that align with learners' developmental needs.

(4) Reconsider Assessment Frameworks to Include Agentive Behaviors

Traditional assessments that focus solely on accuracy or fluency may overlook important indicators of learner agency, such as initiative-taking, negotiation, persistence, and strategic use of AI tools. Future assessment practices should integrate measures that capture these sociotechnical competencies.

7.2 Limitations and directions for future research

Several limitations warrant mention. The study's sample size and specific AI platform limit the generalizability of findings across different populations and systems. Additionally, the qualitative nature of the data restricts conclusions regarding causality. Future research could incorporate mixed methods designs, longitudinal analyses, or cross-platform comparisons to further validate and extend the action-chain model. Investigating emotional, identity-related, or sociocultural dimensions of agency in AI-mediated environments also represents a promising avenue.

7.3 Final remarks

As AI becomes increasingly integrated into educational practice, rethinking learner agency is both timely and necessary. This study demonstrates that agency in virtual language learning environments is co-constructed, distributed, and transformable, emerging through negotiated interactions between human learners and intelligent systems. By illuminating the mechanisms through which agency is compressed, distributed, and regenerated, the study contributes to a deeper understanding of how learners learn with—and not merely through—AI. The proposed framework offers a foundation for designing AI-mediated learning ecologies that not only enhance linguistic development but also empower learners to act intentionally, critically, and creatively in an AI-rich world.

Conflict of Interest

The authors declare that they have no conflicts of interest to this work.

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