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THE COGNITIVE PROCESS MODEL OF WRITING THROUGH A TRIADIC INTERACTION FRAMEWORK IN GENAI-MEDIATED COMPOSITION

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ABSTRACT

The rapid ascension of generative artificial intelligence (GenAI) has transitioned technology from a passive editing tool into an active, co-creative agent. However, traditional composition theories, most notably Flower and Hayes' (1981) model, remain bound to a dyadic framework restricted to the human writer and text. This theoretical disconnect fails to account for the distributed cognitive workflow of human-ai collaboration, leaving a critical architectural gap in writing research, particularly within anxiety-prone English as a foreign language (EFL) contexts. To bridge this gap, this conceptual paper synthesizes distributed cognition and cognitive load theory to propose the triadic interaction framework. This extended model restructures traditional composition by delineating three interconnected operational loops, the prompt/audit, generation, and authorship/ownership loops while updating the internal mental manager into a metacognitive AI monitor. By formalizing GenAI as an externalized working memory and cognitive scaffold, this framework offers a robust theoretical vocabulary for modern composition pedagogy.

Keyword: Cognitive process; Generative AI; triadic interaction framework; distributed cognition; metacognitive AI monitor; EFL writing

1. INTRODUCTION

For over four decades, the Cognitive Process Model of Writing formulated by Flower and Hayes (1981) has served as the foundational bedrock for understanding the internal, non-linear, and recursive mental operations of writers. By decomposing writing into three primary structural pillars the writer's long-term memory, the task environment, and the core cognitive processes of planning, translating, and reviewing this landmark framework successfully shifted the composition paradigm from a product-oriented view to a process-oriented exploration of cognitive mechanics. Subsequent theoretical advancements further established that written composition is an evolutionary act of knowledge transformation rather than mere information retrieval (Bereiter & Scardamalia, 1987), requiring intense self-regulation, structural orchestration, and severe demands on central executive resources (Kellogg, 1996; McCutchen, 1996).

However, the rapid ascension and institutional infiltration of Generative Artificial Intelligence (GenAI), powered by Large Language Models (LLMs), has triggered a monumental paradigm shift in educational technology (UNESCO, 2023). AI has drastically evolved from a passive, rule-based error correction tool, such as basic spell checkers, automated essay scoring systems, or static corpus-based software (e.g., Grammarly) into an active, co-creative agent capable of generating sophisticated discourse, structuring complex academic arguments, and offering human-like formative feedback. Recent empirical exploration demonstrates that GenAI possesses unprecedented dialogic capabilities, allowing users to engage in dynamic interactive loops that completely reshape literacy practices. In the contemporary writing landscape, GenAI no longer sits on the periphery of the task environment; instead, it fundamentally intertwines with the writer's cognitive workspace, operating as an autonomous co-writer that actively participates in, alters, and co-constructs the internal processes of human thought.

Despite the profound empirical changes in how students compose essays in the digital age, a critical theoretical disconnect persists. Traditional cognitive writing models, including the classic

Flower and Hayes (1981) model and its subsequent influential revisions (e.g., Hayes, 1996), are fundamentally predicated upon a dyadic interaction framework a closed cognitive ecosystem exclusively comprising the human Writer and the evolving Text. Within this conventional boundary, all cognitive planning, linguistic translation, and evaluative monitoring are assumed to be generated solely within the biological constraints of the human mind, operating under a limited working memory capacity (Baddeley, 2000).

This dyadic assumption fails to capture the contemporary reality of AI-mediated writing. Emerging literature indicates that the inclusion of GenAI disrupts the traditional cognitive workflow, yet existing models lack the architectural capacity to map how cognitive load is distributed when an external, artificial intelligence acts as a dynamic interlocutor (Sweller, 1998). Crucially, in English as a Foreign Language (EFL) contexts, academic writing is characterized by severe cognitive complexity and extensive psychological strain (MacIntyre & Gardner, 1994). Recent empirical evidence underscores that EFL learners struggle intensely with affective barriers; for instance, writing anxiety heavily hinders writing achievement (Luu & Nguyen, 2026), and sustaining writing motivation requires substantial pedagogical and cognitive scaffolding (Luu & Bui, 2026). While GenAI possesses the technical capacity to mitigate these cognitive and affective burdens by scaffolding language generation, current writing theories offer no structural explanation for how the internal monitoring mechanism of a writer adapts to, evaluates, or relies on an external generative entity. There is an urgent, unaddressed theoretical gap demanding a reconceptualization of cognitive writing boundaries to formally accommodate the active presence of GenAI within the cognitive architecture of composition.

To bridge this gap, this conceptual paper aims to theoretically extend the classic Flower and Hayes (1981) model by proposing a Triadic Interaction Framework that maps the symbiotic relationship between three distinct nodes: the Writer, the GenAI, and the Text. Grounded in the tenets of Distributed Cognition (Hutchins, 1995) and Cognitive Load Theory (Sweller, 1988), this extended model conceptualizes GenAI not merely as an external tool within the task environment, but as an externalized working memory and an active cognitive scaffold that dynamically transforms the nature of planning, translating, and reviewing.

The significance of this paper is twofold. Theoretically, it advances applied linguistics and cognitive psychology by modernizing a classic framework to match the technological realities of the 2020s, offering a rigorous conceptual vocabulary to explain human-AI collaboration in writing. Pedagogically, by delineating how the human Monitor must evolve into a metacognitive supervisor of AI outputs, this framework provides educators with a solid conceptual foundation to move away from restrictive, punitive policies toward process-based, anxiety-sensitive, and AI-literate instructional designs. To guide this theoretical exploration, this paper addresses the following three interconnected research questions:

RQ1: How does the integration of Generative AI alter the traditional cognitive stages of planning, translating, and reviewing in written composition?

RQ2: In what ways does AI function as an external working memory and cognitive scaffold for language learners during the writing process?

RQ3: What theoretical extensions are required to adapt existing cognitive writing models to AI-mediated writing environments?

2. THEORETICAL APPROACH AND METHODOLOGY

Rather than relying on empirical data collection and statistical analysis standard in experimental designs, this conceptual paper employs a qualitative, theory-building methodology grounded in Conceptual Analysis and Theoretical Synthesis (Jaakkola, 2020; MacInnis, 2011). Conceptual papers serve a distinct and vital role in applied linguistics by reorganizing existing observations, exposing boundaries in traditional paradigms, and mapping out fresh interconnected frameworks. To systematically achieve the expansion of the Flower and Hayes (1981) model, this section delineates the explicit methodological protocol utilized: the conceptual analysis method, the strict literature selection criteria, and the structural analytical matrix used to contrast classic cognitive stages with GenAI interactions.

2.1. Conceptual Analysis Method

The primary methodology utilized is Conceptual Analysis & Revision, which involves scrutinizing the underlying assumptions of an established framework and modifying its structural components to accommodate a novel, highly disruptive phenomenon—in this case, Generative AI (MacInnis, 2011). The logical reasoning process operates on a two-fold approach:

1. *Deconstruction:* Meticulously mofifying the original sub-components of the Flower and Hayes (1981) model (Internal Long-Term Memory, the Task Environment, and the cognitive trio of Planning, Translating, and Reviewing under the internal Monitor).
2. *Theoretical Intersection:* Intersecting these components with the core tenets of Distributed Cognition Theory (Hutchins, 1995; Salomon, 1993). This lens posits that human cognitive processes are not restricted to individual biological brains but can be fundamentally distributed across social and technological artifacts.

By utilizing distributed cognition as an analytical tool, this paper systematically evaluates how cognitive load shifts from an internal operation to an externalized, collaborative human-AI workspace, thereby establishing the logical necessity for a triadic framework.

Literature Selection Criteria

To ensure a rigorous, transparent, and comprehensive foundation for this conceptual inquiry, literature was selected using a targeted multi-perspective search strategy across major indexes (Scopus, Web of Science, and Google Scholar). The selection was bound by strict inclusion criteria divided into two explicit categories:

- Foundational Cognitive Psychology of Writing. This includes seminal, highly cited works that establish the mechanics of working memory, cognitive load, and traditional composing processes (e.g., Baddeley, 2000; Bereiter & Scardamalia, 1987; Flower & Hayes, 1981; Hayes, 1996; Kellogg, 1996; McCutchen, 1996).

- State-of-the-Art Human-AI Composition (2023–2026). This captures the immediate, evolving realities of Large Language Models in educational technology, second language writing, and Human-Computer Interaction (HCI). Priority was given to peer-reviewed papers addressing prompt engineering, cognitive load modification, and the socio-ethical boundaries of GenAI integration (Sweller, 1998).

Papers that treated AI merely as a statistical grading tool (Automated Essay Scoring) without examining the student's internal cognitive behavior were explicitly excluded.

To guarantee an objective, structured comparison between the traditional dyadic model and the new AI-mediated reality, the conceptual synthesis was systematically operationalized through an Analytical Matrix (Table 1). This matrix directly charts the classic, internal cognitive operations against the newly emerged, externalized AI interactive behaviors.

Table 1. *The Analytical Alignment Matrix between Traditional Cognitive Components and GenAI Operations*

Classic Flower & Hayes (1981) Component	Traditional Dyadic Definition (Human ↔ Text)	GenAI Interactive Behavior	Reconceptualized Triadic Dimension (Writer ↔ GenAI ↔ Text)
Planning	Internal goal-setting, organizing, and idea generation isolated within the mind.	Prompt Engineering: Formulating directives, setting constraints, and iterating conversational cues.	Co-Constructed Scaffolding: Dialogic planning where AI offers structural ideation and human selects/refines.
Translating	Converting abstract internal semantic concepts into visible orthographic text.	Automated Text Generation / Expansion: AI converts prompts into syntactic prose instantly.	Collaborative Co-Drafting: Human acts as a stylistic manager, directing AI text expansion and phrasing.

Reviewing	Diagnostic evaluation of text followed by recursive editing/correction.	Formative Feedback / Rapid Prompt Iteration: AI highlights discrepancies; human re-prompts for fixes.	Critical Output Evaluation: High-stakes human auditing of AI accuracy, authorship, and academic integrity.
The Monitor	Internal metacognitive manager regulating switches between stages.	Human-in-the-Loop Supervision: Human monitors when to intervene or defer to the AI agent.	Metacognitive AI Monitor: Supervision expanded to control both human cognitive flow and external AI loops.

Through this matrix, each subsequent section of this paper maps these alignments, constructing a robust theoretical bridge that shifts composition theory from a self-contained mental act to an integrated, distributed socio-technical process.

3. THE CLASSIC MODEL: A CRITICAL REVIEW

To evaluate how Generative Artificial Intelligence (GenAI) alters the cognitive architecture of composition, it is necessary to first deconstruct the standard baseline. The classic Cognitive Process Model of Writing formulated by Flower and Hayes (1981) conceptualizes writing not as a linear progression, but as a highly recursive, non-linear mental phenomenon governed by three structural pillars. A static internal repository where the writer stores knowledge of the topic, awareness of the intended audience, and internalized operational writing plans or rhetorical schemas.

An external domain consisting of everything outside the writer's immediate biological mind. This is traditionally restricted to the *rhetorical problem* (the writing assignment, prompt, and target audience) and the *text produced so far* (the physical text accumulating on the page or screen). The core operational engine where the actual mental labor takes place, divided into three recursive sub-processes:

- Generating abstract ideas, setting goals, and organizing concepts.

- Converting those internal, non-verbal semantic ideas into visible orthographic text.

- Diagnosing errors and revising the produced text through reading and editing.

Crucially, all three sub-processes are monitored and regulated by an internal Monitor a metacognitive manager inside the writer's brain that decides when to switch from planning to translating, or when to interrupt draft generation to review a sentence.

While this dyadic structure successfully explained the mechanics of traditional writing, it exhibits severe theoretical limitations when applied to modern AI-mediated environments.

First, the recursive, non-linear nature of the model is structurally disrupted. In the classic model, recursivity is driven entirely by human executive control the writer chooses to pause writing because they realize an idea needs re-planning. However, when interacting with Large Language Models (LLMs), the traditional sequence is fragmented. GenAI can execute the translating phase instantaneously from a rudimentary prompt, allowing the writer to skip original sentence generation entirely and jump straight into high-level reviewing. This automated leaps break the cognitive progression assumed by Flower and Hayes.

Second, the boundary between the Writer's Long-Term Memory and the Task Environment is heavily blurred. Traditionally, the task environment was passive (paper or a word processor). Today, GenAI acts as an active, externalized repository of global knowledge and linguistic structures. When a writer drafts an essay with an AI assistant like Wordtune or ChatGPT, they no longer rely solely on the linguistic data stored in their biological LTM; instead, they query an externalized digital database that provides real-time vocabulary, syntax, and ideation (Nazari et al., 2021; Zhao, 2022). Consequently, the long-term memory node is no longer exclusively internal, exposing a profound conceptual gap in the 1981 model.

4. RECONCEPTUALIZING THE COGNITIVE STAGES UNDER AI INTEGRATION

The integration of GenAI shifts writing from an individual mental monologue into a dynamic, dialogic human-machine collaboration. This transformation fundamentally alters the planning, translating, and reviewing stages.

Planning stage

In the traditional framework, planning is an internal act of retrieval and organization. Under AI integration, planning externalizes into Prompt Engineering. Instead of generating topics and organizational outlines purely from internal cognitive resources, the writer must formulate explicit directives, establish contextual constraints, and design conversational cues for the AI agent. Planning becomes an iterative, dialogic process: the human writer sets a preliminary goal, the AI generates structural alternatives, and the human filters and refines the output. The cognitive load at this stage shifts from *retrieving semantic information* to *synthesizing, structuring, and directing algorithmic responses*.

Translating stage

Translating was historically defined as the high-load cognitive burden of converting abstract mental propositions into formal orthographic language, a phase particularly exhausting for second language writers due to limited linguistic automaticity (McCutchen, 1996). With GenAI, the human writer is largely liberated from translating text from scratch. By supplying a prompt, the writer delegates the mechanical execution of syntax, morphology, and lexical retrieval to the machine (Gayed et al., 2022). The human role transitions into a stylistic manager and co-drafter. The cognitive task here is no longer linguistic generation, but rhetorical steering, monitoring whether the AI's rapid text expansion matches the target tone, register, and communicative objective.

Reviewing stage

In traditional models, reviewing is often treated as an intermittent, lower-priority clean-up phase focused on localized syntax and surface errors (Flower & Hayes, 1981). In AI-assisted writing, this dynamic is inverted: reviewing becomes the most cognitively demanding and vital phase of composition. Because GenAI frequently generates plausible-sounding but factually inaccurate or rhetorically shallow prose often referred to as algorithmic hallucinations (Rudolph et al., 2023) the human writer cannot accept outputs passively. Reviewing shifts from basic grammar editing to Critical Output Evaluation. The writer must engage in high-stakes cognitive auditing, rigorously evaluating the AI's text for accuracy, voice, authorial alignment, and academic integrity (Thorp, 2023).

5. AI AS AN EXTERNAL WORKING MEMORY AND COGNITIVE SCAFFOLD

To understand how a writer manages this altered cognitive workflow, composition theory must integrate the paradigms of Distributed Cognition (Hutchins, 1995) and Cognitive Load Theory (Sweller, 1988).

Distributed cognition argues that human intelligence is not confined to the skull but is shared across technological tools (Salomon, 1993). In this extended model, GenAI functions as an externalized working memory. Biological working memory has severe capacity limitations, capable of holding only a few chunks of information simultaneously (Baddeley, 2000). During academic composition, an EFL writer often experiences cognitive overload as they try to balance sentence structure, vocabulary choice, and paragraph coherence concurrently (Luu & Nguyen, 2026).

By offloading the immediate burden of grammatical construction and sentence expansion to an AI writing assistant, the writer effectively bypasses these biological constraints (Sweller, 1998). The AI maintains the complex linguistic structures and structural cohesion in its digital workspace, freeing up the human writer's central executive resources to focus on macro-level argumentation and critical synthesis.

GenAI acts as a dynamic cognitive scaffold within Vygotsky's Zone of Proximal Development (ZPD). For language learners who experience high levels of writing anxiety due to inadequate linguistic knowledge (Luu & Nguyen, 2026), AI tools offer contextual support. By generating real-time synonyms, clarifying idiomatic expressions, and offering immediate structural alternatives, the AI provides a personalized linguistic scaffold (Gayed et al., 2022; Zhao, 2022). This allows learners to produce academic texts that surpass their independent biological capabilities, lowering affective barriers and enhancing writing self-efficacy.

6. THE PROPOSED TRIADIC MODEL OF AI-MEDIATED WRITING

To formally integrate these distributed operations, this paper proposes a Triadic Interaction Framework (Figure 1). This framework expands the traditional human-text dyad into a three-way, interconnected cognitive ecosystem.

The model consists of three distinct interaction loops. The writer directs the AI via prompt engineering, and the AI returns generated prose or formative feedback. The human continually reviews and re-prompts, creating an iterative dialogic cycle. The AI algorithm processes the constraints provided by the writer and directly alters the state of the text, executing automated expansions, structural rewrites, or stylistic polishing. The classic relationship where the human reads, evaluates ownership, checks for authenticity, and retains final authorial control over the evolving document.

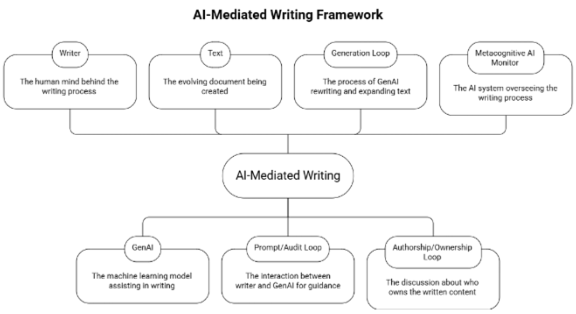

Figure 1. Triadic Interaction Framework

The most radical architectural change in this model is the evolution of the control center. In the 1981 model, the Monitor was an internal mental switchboard directing internal cognitive traffic. In the Triadic Model, this component is updated into the Metacognitive AI Monitor.

This evolved monitor does not just manage human attention; it actively regulates the division of cognitive labor between the human mind and the machine. It dictates *when* to execute a task independently, *when* to delegate linguistic generation to the GenAI, and *how* to critically audit the machine's output. The Metacognitive AI Monitor is the ultimate cognitive safeguard, ensuring that the human writer remains in-the-loop as an active supervisor rather than a passive consumer of automated text.

7. CONCLUSIONS

This conceptual paper modernizes composition theory for the digital era by extending the classic, biological boundaries of Flower and Hayes' (1981) model into the Triadic Interaction Framework. Grounded in Distributed Cognition and Cognitive Load Theory, this framework dismantles the traditional human-text dyad, positioning Generative AI not merely as an external tool, but as an active cognitive scaffold and externalized working memory that fundamentally redistributes cognitive labor across three operational loops: the Prompt/Audit Loop, the Generation Loop, and the Authorship/Ownership Loop. The core theoretical contribution lies in updating the traditional internal control center into a Metacognitive AI Monitor, which serves as a vital safeguard regulating when to delegate tasks and how to critically audit algorithmic output against hallucinations. Pedagogically, this model provides university educators, particularly in anxiety-prone EFL contexts with a rigorous, process-based foundation to transition from punitive anti-AI policies toward instructional designs that foster AI literacy and ensure the human writer remains securely and actively in-the-loop.

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