Studies in Second Language Learning and Teaching
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SSLLT 0 (0). 2026. 1-27. Published online: 01.09.2026
https://doi.org/10.14746/ssllt.53662
http://pressto.amu.edu.pl/index.php/ssllt

Feedback in second language writing: Current issues in research and practice

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Abstract

This article reconceptualizes feedback in second language (L2) writing for an era of digital and multimodal composing. It argues that feedback must extend beyond error correction to address communicative effectiveness, design, and intermodal coherence (e.g., image-text alignment). To situate our discussion within the evolving ecology of digitally-mediated writing support, the article first introduces affordances of generative artificial intelligence (GenAI) tools for feedback and describes how AI can be used to support feedback practices. The article also accounts for the complexity of feedback in contemporary composing environments by drawing on several complementary frameworks: cognitive and sociocultural perspectives, which explain internal and socially-mediated processing of feedback (e.g., attention, noticing, cognitive load, mediation), and informs multimodal feedback practices. In particular, it focuses on learning by design, which positions feedback as a means of developing learners as active designers of meaning, and on D'Angelo's (2016) model, which provides criteria for feedback provision on multimodal products. Pedagogically, the article operationalizes these perspectives through examples that illustrate how instructor and AI feedback can be integrated to support revision in both monomodal and multimodal texts in L2 learning and teaching contexts. The article concludes by proposing a research agenda that calls for longitudinal investigation of AI-mediated and multimodal feedback ecologies and examines how learner characteristics shape the effective and ethical use of feedback in L2 classrooms.

Keywords: monomodal/multimodal feedback; infographics; human- and AI-mediated feedback; feedback processing; D'Angelo model; learning by design

1. Introduction

We are witnessing a global reconceptualization of feedback in second language (L2) writing and composing, its definition, mechanisms, and modes. Historically, feedback was primarily corrective, targeting grammatical and lexical errors through direct or indirect reformulations, and only secondarily addressing global concerns, such as content and structure, particularly in classroom settings (Oskoz & Elola, 2020). Contemporary composing practices, including multimodal texts (e.g., blogs, infographics, podcasts), however, extend beyond language accuracy and writing conventions to encompass design, visual orchestration, discourse structure, stance, and affect (Elola & Oskoz, 2023; Kress, 2010; The New London Group, 1996). This expansion has shifted feedback from a narrow focus on error remediation to a broader concern with communicative effectiveness and multimodal design (Elola & Oskoz, 2022), which is prompting instructors to reconsider their feedback practices to address the specific compositional demands of multimodal texts (Hafner, 2014). In the ever-evolving technological context, we need to keep in mind that although instructor feedback remains central, computational systems, including grammar/usage checkers and large language models (LLMs), increasingly mediate how learners access, interpret, and apply feedback. For instance, recent advances in artificial intelligence (AI), that is, systems designed to emulate cognitive processes, such as pattern recognition, learning, and problem solving (Baker et al., 2019), have further expanded the role of feedback within the writing process. Furthermore, the inclusion of computational systems foregrounds questions of validity, bias, explainability, and learner agency (e.g., Koltovskaia et al., 2024). Feedback with these new tools needs to be seen as information that instructors and learners analyze to make decisions, rather than as messages to follow without question. Importantly, this paper is grounded in the field of second language learning and teaching, with a particular focus on how feedback, especially AI-mediated feedback, shapes learners' development as writers and meaning-makers in instructional contexts. This emphasis responds to the central concerns of L2 pedagogy and ensures alignment with the aims and scope of research in second language learning and teaching.

In Elola and Oskoz's (2022) article, we framed feedback primarily through multiliteracies and the learning by design (LbD) framework, positioning learners as active designers of meaning and foregrounding revision as an iterative process of redesign across modes. That perspective remains foundational. However, as feedback practices become increasingly mediated by AI systems and distributed across digital environments, multiliteracies alone do not fully account for the cognitive and interactional dynamics involved in processing, interpreting, and enacting feedback. In this paper, we therefore extend our earlier position by placing LbD in conversation with additional theoretical lenses that help illuminate dimensions left underexplored in our prior work. We draw on different theoretical and pedagogical perspectives, each of which helps explain a different dimension of feedback. Specifically, cognitive and sociocultural perspectives clarify how learners allocate attention, notice gaps, manage cognitive load, and engage in mediated meaning-making when working with responses to their writing (Elola, 2026). D'Angelo's (2016) model enables closer analysis of the multimodal artifact itself, offering a framework for examining coherence, modal orchestration, and communicative impact. At the same time, multimedia learning theory further explains how modality shapes processing when information is presented across written, visual, and auditory channels – an increasingly common feature of AI-mediated environments. Rather than displacing LbD, these perspectives expand it: They help specify the cognitive conditions under which redesign occurs, the modal principles that shape comprehension, and the textual features that signal effective design. Taken together, these perspectives provide complementary insights into how feedback operates in classrooms, including when emerging technologies like AI are integrated.

Accordingly, this paper examines how feedback can be reconceptualized in contemporary L2 writing and composing by bringing together theoretical and pedagogical perspectives that account for monomodal, multimodal, and AI-mediated feedback practices. In doing so, we explore how AI tools are reshaping feedback processes, learners' engagement with feedback, and instructors' roles within increasingly digital and multimodal learning environments. Throughout this paper, we focus on how AI tools are reshaping feedback practices in L2 learning and teaching contexts and shifting the instructor's role in providing feedback. To illustrate how learners may also benefit from AI feedback, this paper draws on two related tasks that move from monomodal to multimodal composing. One example involves a traditional monomodal written composition (see Figure 2), allowing us to examine how feedback operates on linguistic form, organization, and meaning-making within a monomodal text. A second example focuses on the design of an infographic (see Figure 3), in which learners construct meaning and receive feedback on the orchestration of visual, textual, spatial, and temporal resources. Before elaborating on these frameworks and the pedagogical examples in detail, we first examine the affordances of AI tools, especially ChatGPT as currently the most widely used generative AI (GenAI) system in L2 contexts, to situate our discussion within the evolving ecology of digitally mediated writing support.

2. AI walks into the writing room

Today's AI-enabled writing tools have become part of the L2 writing landscape, particularly when it comes to L2 feedback. They are, however, not interchangeable as AI tools differ in their underlying models, feedback precision, modality support, and capacity to scaffold learners' revision processes, resulting in varying pedagogical implications for feedback provision. For instance, they differ in their affordances and in whether and how they support monomodal or multimodal feedback (see Figure 1) at various stages of the composing and feedback process. Some tools, for instance, focus primarily on providing monomodal feedback to improve linguistic accuracy and clarity in written texts. For example, Grammarly and Microsoft Editor provide real-time feedback on grammar, punctuation, concision, tone, and clarity, helping writers refine academic and professional prose. Similarly, ProWritingAid offers more detailed stylistic diagnostics, including reports on structure, lexical repetition, and transitions, which can support deeper revision and reflection. Tools developed specifically for academic writing, such as Writefull and Scribbr's AI Assistant, draw on large corpora of scholarly texts to offer feedback aligned with disciplinary conventions, helping writers improve coherence, phrasing, and overall readability. Furthermore, other platforms like Elicit.org, extend feedback beyond sentence-level concerns by assisting with literature review processes, locating relevant research, and helping writers refine arguments and conceptual organization.

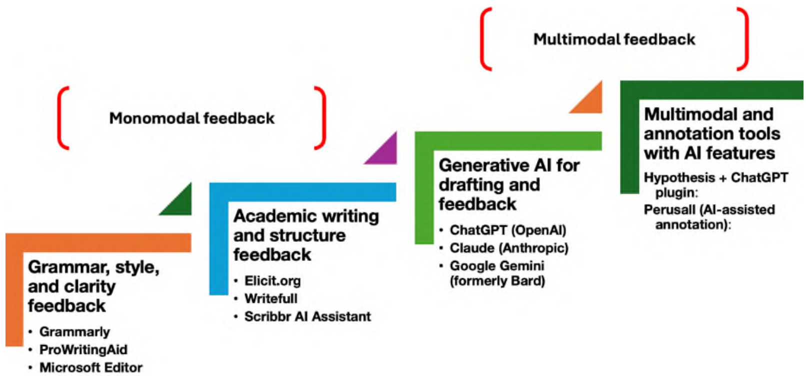

Figure 1 The affordances of tools for monomodal and multimodal feedback

LLMs, including ChatGPT, Claude, and Google Gemini, can generate and respond to feedback on content, organization, tone, and argumentation when guided by targeted prompts in monomodal and multimodal formats. Recent advances in generative AI have further expanded the scope of feedback by enabling more interactive, dialogic, and multimodal forms of support (Koltovskaia et al., 2024). In addition to supporting monomodal writing, AI tools are increasingly integrated into multimodal workflows. For instance, platforms like Synthesia enable AI-generated video feedback and demonstrations, while annotation tools, including Hypothesis and Perusall, support collaborative feedback through social annotation and discussion. Taken together, these tools illustrate how feedback is no longer limited to static written comments but can be delivered dynamically across modalities and platforms. These tools allow writers to engage in iterative feedback cycles, refining their texts through ongoing interaction. As AI becomes more integrated into writing and revision practices, both instructors and learners must navigate a broader range of feedback sources, each offering distinct affordances that shape how feedback is interpreted, applied, and incorporated into the composing process.

3. The role of ChatGPT in L2 feedback

Recent studies portray ChatGPT, the most widely analyzed tool to date, as a capable feedback partner across multiple stages of writing development. Current research has indicated that it can diagnose strengths and weaknesses, propose targeted revisions (Zeevy-Solovey, 2024), infer the main idea of the text, and deliver both corrective and content-focused feedback, often offering concrete examples or even a revised draft (Pérez-Núñez, 2023). Beyond global guidance, ChatGPT can help evaluate clarity, focus, structure, coherence, and cohesion (Barrot, 2023; Yoon et al., 2023); meanwhile, at the sentence level, it supports grammatical accuracy, clarifies meaning, and suggests alternative expressions (Su et al., 2023). Research also shows that ChatGPT feedback tends to be readable and easy to follow, which helps learners understand and act on suggestions. Importantly, it can also generate process-oriented guidance that supports iterative revision and reflection (Dai et al., 2023).

Recent studies show a nuanced stance toward AI-generated feedback from the learner's perspective. Learners tend to favor a balanced approach, combining peer and instructor feedback with support from ChatGPT, rather than relying on AI alone (Dai et al., 2023; Zeevy-Solovey, 2024). They often perceive AI as less trustworthy than human feedback (Zeevy-Solovey, 2024), yet they recognize its affordances, particularly its immediacy, adaptive responses, and capacity to stimulate critical and logical thinking (Bok & Cho, 2023; Mahapatra, 2024; Meniado et al., 2024; Xiao & Zhi, 2023; Zou & Huang, 2023). Many learners especially value the opportunity to engage with instant, low-stakes feedback that allows them to reflect and revise before submitting a final draft.

This growing body of research also highlights important limitations that instructors must carefully consider when integrating generative AI into feedback practices. Although AI tools can provide rapid and accessible responses, studies show that generative AI systems may produce inaccurate or inconsistent judgments, with identical input sometimes generating different responses, which can undermine the stability needed to support sustained revision (Dai et al., 2023; Su et al., 2023; Zeevy-Solovey, 2024). These concerns extend beyond reliability to broader pedagogical and ethical issues, including questions of authorship, originality, and academic integrity (Pérez-Núñez, 2023). Equally important, AI feedback often prioritizes surface-level features, such as grammar and mechanics, while providing less support for rhetorical development, voice, and meaning-making. As a result, its feedback can be vague or abstract, requiring instructor mediation to become pedagogically meaningful (Su et al., 2023). When explanations lack depth, learners may implement suggested changes without fully understanding them, limiting opportunities for reflection and reducing the potential for long-term development.

These limitations underscore the continued importance of instructor guidance in helping learners interpret, evaluate, and act on AI-mediated feedback in intentional and critical ways. Due to the integration of multimodal texts, instructors need to develop familiarity with multimodal and visual frameworks that allow them to address both the linguistic and non-linguistic aspects of learners' compositions. They also need working knowledge of AI and multimodal tools to accommodate diverse learner preferences, reduce cognitive load, and design tasks that integrate feedback purposefully. When guided effectively, AI has the potential to complement instructor feedback by streamlining routine feedback, allowing instructors to focus on higher-order elements, such as argument, organization, and multimodal design.

Learners, in turn, require structured support to interpret and apply feedback that targets both linguistic accuracy and multimodal design. Learners need to be supported in critically evaluating AI suggestions, making informed decisions about when to accept, adapt, or reject revisions based on their communicative goals and intentions (Su et al., 2023). This critical engagement becomes especially important because LLMs, trained on extensive text corpora using transformer architectures and attention mechanisms (Devlin et al., 2019; Vaswani et al., 2017), may drift from the writer's intended meaning when prompts are vague or underspecified. As a result, learners benefit from learning how to formulate clear and purposeful prompts that guide the system toward more relevant and meaningful feedback (Atlas, 2023). That is, effective use of AI involves an iterative process in which learners refine their prompts, request clarification or justification, and evaluate whether suggested changes align with their rhetorical and design goals. Through this process, AI becomes not a replacement for the writer's judgment but a tool that supports reflection, strengthens authorial decision-making, and reinforces learner agency. Instruction should promote critical AI literacy or the capacity to identify inaccuracies and biases, detect missing or weak personal voice, craft more effective prompts, and recognize the limits of AI-generated feedback. Cultivating this literacy helps learners to see AI as a resource to reason with, not a voice to obey.

Through this combination of pedagogical scaffolding, reflective practice, and critical awareness, both instructors and learners can make the most of AI feedback affordances. When approached thoughtfully, AI feedback may become not a shortcut but a pedagogical partner, a tool that can support learner agency, deepen understanding of revision processes, and contribute meaningfully to the development of writing and multimodal literacy in L2 classrooms. At the same time, these evolving feedback practices raise important theoretical questions about how learners interpret, regulate, and act, as discussed in the next section.

4. Feedback processing in human-AI contexts

Although feedback in L2 writing traditionally has been examined through cognitive and sociocultural lenses (Elola & Oskoz, 2022), the changing ecology of digital and AI-mediated composing environments invites a broader theoretical conversation. Earlier models were developed largely to account for instructor comments on alphabetic texts, often assuming relatively stable modes of delivery and interaction. However, feedback is now increasingly distributed across platforms, modalities, and human-AI collaborations, requiring frameworks that can address both processing and design. Cognitive and sociocultural perspectives remain central for explaining how learners attend to, interpret, and regulate feedback, particularly in relation to linguistic form and meaning-making. Beyond processing, product-oriented approaches, including D'Angelo's (2016, 2018) model, provide analytical tools for examining how feedback supports the coherence, orchestration, and communicative impact of multimodal texts. Finally, multiliteracies-oriented frameworks like LbD foreground learners' role as designers of meaning, positioning feedback as part of an iterative, transformative process rather than as a corrective endpoint (Cope & Kalantzis, 2015). At the same time, the growth of multimodal feedback formats, such as screencasts, annotated visuals, and AI-generated explanations, raises questions about how learners manage information presented across written, visual, and auditory channels. Together, these perspectives help reframe feedback not simply as commentary on language but as a dynamic, multimodal, and increasingly technologized practice. To understand how these perspectives complement one another, it is useful to examine the cognitive and social processes that underpin learners' engagement with feedback.

4.1. Feedback as a cognitive and social activity

Understanding feedback in contemporary L2 writing requires accounting for both internal cognitive regulation and external social mediation. Classic cognitive models still anchor our understanding, framing writing as a recursive, goal-directed process – planning, translating, revising – coordinated by working memory and executive control (Flower & Hayes, 1980; Kellogg, 1996). In terms of feedback, cognitive models help explain how feedback interacts with planning, drafting, and revising, depending on task demands and proficiency. However, as composing practices increasingly involve digital and multimodal forms, traditional text-based conceptions of feedback are no longer sufficient to capture the full complexity of contemporary writing. Writers must now coordinate linguistic, visual, and other semiotic resources, and feedback must support not only linguistic accuracy but also coherence across modes, design effectiveness, and audience engagement.

Within the current technological context, the emergence of automated feedback tools, machine translation, and generative AI systems like ChatGPT has transformed how writers access and engage with feedback. Rather than receiving feedback solely at discrete stages, learners can now interact with feedback iteratively throughout the composing process, receiving real-time suggestions that support revision, reflection, and experimentation. AI tools allow feedback to be more closely aligned with learners' developmental needs, offering differentiated support that can adapt to varying levels of proficiency and rhetorical goals. LLMs, for instance, can analyze linguistic patterns and generate human-like language. In doing so, they redistribute aspects of cognitive work across the writing cycle by supporting planning, language generation, evaluation, and revision. Rather than replacing the writer's cognitive effort, these tools reshape how writers engage with feedback, creating opportunities for more sustained regulation, strategic decision-making, and multimodal meaning-making.

As writers engage with AI-supported environments, tools like ChatGPT increasingly become part of how they plan, monitor, and revise their work, influencing decision-making in both monomodal and multimodal composition (Elola, 2026; Overstreet et al., 2023). When drafting a monomodal text, grammar and style checkers, such as Grammarly and LLM copilots, help writers identify linguistic and organizational issues, from morphosyntactic accuracy and lexical choice to cohesion and register. Rather than simply correcting errors, these tools prompt writers to compare alternative formulations and consider how revisions align with their communicative goals, fostering metacognitive awareness of language use (Koltovskaia et al., 2024). As writers move into revision, where feedback plays a particularly influential role, AI tools like Gemini can offer suggestions that extend beyond surface-level corrections to include structural reorganization, refinements in tone and stance, and improvements in multimodal coherence and accessibility (Lim, 2020). By externalizing routine aspects of revision, these tools allow writers to redirect their attention toward higher-order concerns, such as strengthening arguments, refining authorial voice, and enhancing the overall design and effectiveness of their texts (Tan, 2023). In multimodal composing, AI tools increasingly support learners as they coordinate linguistic, visual, and auditory resources to construct meaning. These tools can scaffold semiotic orchestration by suggesting layouts, visual hierarchies, iconography, soundtrack elements, and captioning while also helping writers identify potential coherence issues across modes, such as redundancy or competing focal points (Lim, 2020). In this way, AI-mediated feedback can make aspects of multimodal design more visible, allowing learners to reflect on how different semiotic choices contribute to the overall effectiveness of their message.

As writers engage with AI-supported feedback, revision can become an increasingly active process of attention regulation and decision-making. Rather than simply correcting errors, writers must interpret tool-generated suggestions, evaluate their relevance, and integrate linguistic and visual information in ways that align with their communicative goals. This interaction expands the cognitive architecture of writing as learners navigate multiple sources of input and coordinate revisions across modes (Leijten et al., 2014). Tools like Grammarly, QuillBot, and ChatGPT invite writers to compare alternative formulations, reflect on differences in meaning and tone, and decide whether to accept, modify, or reject proposed changes. In doing so, revision evolves from a primarily corrective activity into a process of strategic problem solving, where learners actively regulate their composing choices. Research suggests that digital feedback environments can support this process by externalizing routine cognitive operations, allowing writers to devote greater mental resources to higher-order concerns, such as cohesion, audience awareness, and multimodal design (Koltovskaia et al., 2024; Overstreet et al., 2023). This redistribution of cognitive effort is particularly significant in multimodal contexts where writers must coordinate linguistic, visual, and auditory elements simultaneously. Although this redistribution of cognitive effort increases the complexity of the composing task, it can also enhance retention and meaning-making by engaging multiple channels of processing, consistent with principles of dual coding (Mayer, 2002).

Recent research increasingly portrays AI-mediated revision as part of a broader feedback ecology in which learners draw on multiple sources to support both linguistic accuracy and multimodal design (Koltovskaia et al., 2024). Within these environments, tools like ChatGPT can offer metalinguistic explanations, suggest alternative structures, and comment on tone or visual coherence, whereas tools like QuillBot invite writers to consider different ways of expressing meaning, prompting reflection on register and rhetorical effect (Su et al., 2023). Rather than replacing instructor feedback, these tools contribute to a more interactive process in which feedback is shaped through ongoing exchanges between the learner's judgment and computational suggestions (Moorhouse & Kohnke, 2024). The developmental value of this feedback ultimately depends on how learners engage with it, whether they critically evaluate suggestions, integrate them thoughtfully, and align revisions with their communicative intentions (Ghafouri, 2024). In this evolving landscape, feedback plays a central role in guiding attention and supporting goal-directed revision. By externalizing routine form-based corrections, digital tools allow writers to redirect cognitive effort toward higher-order concerns, including strengthening message clarity, refining rhetorical choices, and enhancing multimodal coherence.

On July 20, 1969, the world watched with great anticipation as the first man walked on the moon. It was a **historic events t**hat captured the imagination of millions of **person**. Neil Armstrong said the famous phrase: "That's one small step for man, one giant leap for mankind."

Many people still **believes i**t was a key moment for science, and some thinks **t**hat nothing like it will ever happen again. It is essential that people **understands** what it meant. NASA asked that the astronauts **takes s**amples of the lunar soil. They spoke with engineers before traveling, who prepared them for the mission.

The astronauts carry out intensive training, and it was important that each one demonstrates control in difficult situations. Humanity has continued its desire to eventually colonize other planets. The **scienctific** impact remains enormous today.

Figure 2 Apollo composition

To illustrate these ideas, we draw on two related tasks that move from monomodal to multimodal composing: a written composition (see Figure 2) and an infographic (see Figure 3). Together, they demonstrate how feedback operates on linguistic form, organization, and meaning-making within a monomodal text. For the monomodal writing activity, after the pre-writing task, learners write a short 100- to 150-word essay about the first moon landing (see Figure 2). After they complete the essay, learners input it into AI for feedback with two different purposes. First, learners input the essay to find errors in the text. In this first iteration, they ask questions with prompts like the following: "Please identify all the errors on agreement and vocabulary in the text. Mark them only in bold and do not provide the correction." That is, in the first iteration, learners ask AI to signal where there are errors in the text but without any explanation, direct feedback, or metalinguistic comments. The AI tool identifies areas of concern to guide learners' attention but withholds direct feedback and metalinguistic explanation, prompting learners to undertake initial revisions autonomously.

Second, after revising their errors, learners input the essay one more time to receive more explicit feedback at the micro-level (e.g., grammar, vocabulary) from the bolded grammatical errors noted by AI in the previous iteration. Learners can prompt AI with statements like the following: "Please provide explicit correction of my grammatical, vocabulary, and spelling errors." As shown in Table 1, AI during this step retrieves the rule and applies it at the micro-level, providing specific and direct applications.

Table 1 Examples of feedback types generated by AI tools for revision purposes

Issues found in the composition	Cognitive processes and types of feedback
• Agreement: "historic events" → "historic event;" "millions of person" → "millions of people;" "people believes/thinks/understands" → "people believe/think/understand;" "astronauts takes" → "astronauts take;" "each one demonstrates" → "each one demonstrate." • Tense/consistency: Keep past for 1969 actions ("carried out" training) and use present for enduring truths ("remains enormous"). • Diction/Spelling: "scienctific" → "scientific." • Prefer "conducted intensive training" over "carry out intensive training."	• *Selective attention and error detection → rule retrieval → repair (agreement/number issue)* • *Monitoring → retrieval of agreement patterns → metacognitive check (subject-verb agreement)* • *Situation-model building → causal/temporal reasoning → planning (tense/aspect consistency)* • *Lexical retrieval → self-monitoring → orthographic accuracy (lexical precision)*

In a third iteration, learners request feedback at the macro-level on content, organization and register. Learners can prompt AI with questions following various prompts beginning with "Please provide me with the following":

- suggestions of how to improve the content ("Is there anything missing that I should add?");
- suggestions to improve the organization and coherence of the text ("Is there a logical flow in how I connected ideas?" "Do I use appropriate connectors in the text?"); and
- suggestions to ensure that the tone utilized in the text is appropriate for the presentation of the topic of the first moon landing in a formal essay.

As seen in Table 2, AI feedback helps with selective attention and noticing (what is missing), schema activation/building, and causal reasoning (bridge sentences).

Table 2 Examples of types of feedback at the micro- and macro-level generated by AI tools for revision purposes

Issues Found in the Text	Types of Feedback and Cognitive Processes
• Briefly name Apollo 11 and Armstrong/Aldrin/Collins to anchor the event. • Clarify the purpose of soil sampling (scientific analysis) and training (simulations, re-entry, contingencies). • The final two sentences jump from training to colonization; add a bridge (e.g., "Since then…").	Content: *Selective attention and noticing* (what's missing), *schema activation/building*, *causal reasoning* (bridge sentences)
• Logical macro-order (event → quote → significance → preparation → training → legacy). • Transitions between paragraphs are thin. Add guiding phrases to link ideas (e.g., from public reaction to scientific goals, from preparation to lasting impact). • Keep one focus per paragraph: (1) event and quote, (2) significance and public perception, (3) preparation and training, (4) legacy.	Organization: *Macro-planning*, *idea grouping*, *schema organization* (topic → support→wrap)
• Generally informative and neutral, appropriate for a short expository piece. • A few phrases feel casual or vague ("something like it will never happen again"). Prefer precise, academic wording (e.g., "a feat unlikely to be replicated in the same geopolitical context").	Register (tone and appropriateness): *Self-monitoring* (metacognition), *lexical retrieval*, *abstraction* (from colloquial to academic frame)

This example shows how AI-mediated feedback can be interpreted through both cognitive and sociocultural perspectives. From a cognitive view, the first iteration, where AI signals errors without explanation, reduces cognitive load by directing attention to specific problem areas. By narrowing the focus, ChatGPT supports noticing, rule retrieval, and self-repair without overwhelming learners. It thus functions as a scaffold, structuring revision (identify → reflect → revise) and gradually guiding learners toward more explicit rule application. From a sociocultural perspective, AI acts as a mediational tool within the learner's zone of proximal development. The movement from indirect prompts to more explicit micro- and macro-level feedback provides graduated scaffolding that learners can request as needed. This dialogic interaction extends traditional instructor feedback and encourages self-regulation in a low-stakes context. Overall, the example attempts to showcase how AI-mediated feedback supports internal cognitive processes while also serving as an external scaffold that structures revision, reduces overload, and promotes strategic, self-regulated learning.

4.2. D'Angelo's (2016) model assists with multimodal feedback on a multimodal text

This section considers another useful method for providing feedback on multimodal text using the framework of visual metadiscourse developed by D'Angelo (2016), drawing on Hyland's (2000) metadiscourse model and the grammar of visual design (Kress & van Leeuwen, 2020). Whereas D'Angelo (2016) developed her framework to analyze academic posters in biology, medicine, geography, applied linguistics, and economics, this framework recently has been applied in the L2 context. Li et al. (2023), for instance, used it to examine the infographics created by L2 learners of English.

To analyze and classify the linguistic and visual resources employed by poster designers, D'Angelo (2016) developed an ad hoc framework of analysis that provides an excellent basis from which to examine textual and visual strategies. Because a multimodal text combines written and visual components, it requires an analytical framework capable of accounting for how these elements construct meaning. For example, in a multimodal text such as an infographic, the written and visual components do not function independently; rather, they interact to create meaning collectively or, as Kress and van Leeuwen (2020) explain, to establish semantic relationships. For instance, an action verb, such as *look* or *read*, can be expressed by using a visual element (e.g., an arrow or line) pointing at or connecting something. In this way, a writer or composer expresses with images what is usually expressed through writing and vice versa. Sometimes, however, it is not possible to make such changes: The relationship between images and text can be seen as complementary, yet two semiotic codes also can work independently (Kress & van Leeuwen, 2020). To carry out a complete analysis of multimodal texts, one must therefore consider both semiotic codes at the same time, focusing on how they work together for meaning-making purposes. D'Angelo's (2016) framework of visual metadiscourse, which examines both textual and visual features, can be employed to provide feedback on our L2 learners' multimodal texts.

In her analysis of posters, D'Angelo (2018) used Hyland's (2005) theoretical approach to metadiscourse interpretation for the written texts, distinguishing between interactive and interactional resources. Following Hyland (2005), D'Angelo (2018) categorized the textual discourse markers as either interactive (i.e., transitions, frame markers, endophoric markers, evidentials, code glosses) or interactional (i.e., hedges, boosters, attitude markers, self-mentions, engagement markers). Keeping in mind Kress and van Leeuwen's (2020) model of visual elements, D'Angelo also classified visual interactive resources. D'Angelo (2018) noted that authors of multimodal texts can "use visual interactive elements to organize the flow of information and help the viewer in the comprehension of the multimodal text" (pp. 72-73). Focusing on interactive resources, D'Angelo's framework encompasses five categories, that is, information value, framing, connective elements, graphic elements, and fonts, which are further divided into several subcategories.

In an infographic, for instance, information value refers to where the information is located and organized in the layout of a text (e.g., left-right, top-bottom, etc.). The framing, which refers to how we distinguish different sections of the infographic, is done through frame lines, color contrast, and empty space. The ideas presented in the visual and textual discourse of an infographic are linked through connective elements like repetition, vectors, and information alignment, which guide the flow of information presented to the reader in the infographic. Graphic elements also are used to organize or summarize content and help facilitate readers' immediate retention of information. Finally, font decisions, including type, size, and color, are related to legibility, highlighting the important parts of a text and clarifying the organization. In the example below (see Figures 3-7), a learner requests feedback from AI that focuses on genre conventions, organization, layout, colors, and fonts in the infographic. All of these components work together to create a meaningful and thoughtful infographic. For the purposes of this chapter, we focus exclusively on D'Angelo's (2016) visual metadiscourse and how our learners can use AI to receive valuable feedback that enhances their work when used appropriately and critically.

The following example illustrates how learners can use AI to receive feedback on visual metadiscourse features in an infographic. Drawing on D'Angelo's (2016) framework, the example focuses on information presentation, framing, connective elements, graphic resources, and font choices, showing how AI can support multimodal revision. As discussed previously, learners had completed a monomodal writing task related to the first landing on the moon by Neil Armstrong. In a second task based on the content from this monomodal text, learners worked on an infographic about the same topic, this time combining different semiotic resources. After learners completed the first draft, similar to the feedback process they followed with their monomodal text, they input their infographic into AI to receive feedback, requesting comments both on what worked well and what could be improved. Learners input a prompt asking for feedback on the infographic in terms of the following:

- how the information is presented;
- how the different sections of the infographic are distinguished through frame lines, color contrast, and empty space;
- how the ideas presented with images and text are linked through connective elements, such as repetition, vectors, and information alignment;
- how the graphic elements are used to organize and summarize information; and
- how the type, size, or color of the fonts highlight important parts of the text or clarify information.

What is well done:

- The top-bottom structure works effectively. The large title "TITLE" at the top clearly signals the theme, and the information flows downward in three main content sections.
- The layout follows a zigzag reading path (top left → top right → middle right → bottom left → bottom right), which creates movement and keeps the viewer visually engaged.
- The distribution of images (astronaut, moon figure, rocket) across the page balances the composition and prevents text overload in a single area.

What could be improved:

- The left-right positioning lacks clear semantic meaning. Left often suggests "given" information and right "new" information. Here, both sides present new content, which may reduce clarity in hierarchical meaning.
- The main title "TITLE" is too generic and does not communicate the infographic's topic immediately.
- The sections could benefit from clearer progression markers.

Figure 3 Visual metadiscourse AI feedback: Strengths and improvements on information value

What is well done:

- The consistent deep blue background creates strong cohesion.
- Sections are separated naturally through strategic white space, which helps avoid clutter.
- Circular backgrounds around the moon figure and rocket help visually isolate and frame those elements.

What could be improved:

- There are no explicit visual separators (lines, boxes, subtle color shifts) between text sections. The separation relies mainly on spacing.
- The astronaut icon in the middle-left is not framed like the other illustrations, which creates a slight inconsistency in visual framing.
- The similar text formatting across sections makes it harder to distinguish them as separate conceptual units.

Figure 4 Visual metadiscourse AI feedback: Strengths and improvements on framing

What is well done:
- Repetition of circular shapes (moon background, rocket circle) creates visual cohesion.
- The consistent color palette (blue, white, light gray) strengthens thematic unity.
- The alternating placement of images and text creates directional movement across the layout.

What could be improved:
- There are no strong visual vectors (arrows, timelines, directional lines) guiding the reader from one section to the next.
- The infographic would benefit from stronger information alignment–currently, the zigzag flow feels aesthetic rather than logically guided.
- Text blocks are not explicitly connected to the images next to them. Small visual cues (icons, lines, captions) could strengthen semantic connection.

Figure 5 Visual metadiscourse AI feedback: Strengths and improvements on connective elements

What is well done:
- The icons (astronaut helmet, moon figure, rocket) are simple, clean, and easy to recognize.
- Minimalistic graphics reduce cognitive overload and enhance quick comprehension.
- The rocket graphic at the bottom visually suggests progress and forward motion, reinforcing the theme of exploration.

What could be improved:
- The graphics function mainly decoratively rather than informationally. They do not directly visualize specific data.
- The astronaut helmet lacks contextual relevance compared to the other icons.
- Adding a small timeline, labeled diagram, or key facts box would increase informational density and retention value.

Figure 6 Visual metadiscourse AI feedback: Strengths and improvements on graphic elements

What is well done:

- The high contrast (white text on dark blue background) enhances readability.
- The large, bold title is visually dominant and clearly prioritized.
- Font style appears consistent throughout, supporting visual coherence.

What could be improved:

- Important information (e.g., *July 20, 1969*, *Neil Armstrong’s quote*, *NASA*) is not typographically highlighted.
- The font size in the paragraphs may be slightly small for infographic readability.
- There are no typographic variations to signal shifts in topic.

Figure 7 Visual metadiscourse AI feedback: Strengths and improvements on font and typograph

AI, particularly ChatGPT, is playing an expanding role in generating feedback that can reinforce learners’ work and revision practices. In this instance, AI provided specific feedback that addressed all of the learners’ questions, including comments that reaffirm the infographic and comments that can enhance the infographic further. However, as discussed above, such feedback must be engaged with critically because some of the feedback can be too generic (e.g., the main title “TITLE” is too generic and does not communicate the topic of the infographic immediately). Consistent with a multiliteracies orientation, and as presented in the following section, instructors should guide learners in evaluating AI-generated responses thoughtfully and should help them develop a critical stance toward both the feedback they receive and their own learning processes.

4.3. Learning by design

LbD, rooted in multiliteracies theory, offers a powerful framework for embedding feedback into the learning process across four interconnected stages: situated practice, overt instruction, critical framing, and transformed practice (Zapata & Lacorte, 2018). The model, which follows the New London Group’s (1996) curriculum components, includes situated practice (learners experience and notice issues), overt instruction (name and rehearse patterns), critical framing (evaluate suggestions against audience and purpose), and transformed practice (redesign for transfer). Focusing on L2 feedback, (a) situated practice engages learners in authentic writing contexts where feedback – peer, teacher, or AI – emerges organically through real-world communication; (b) overt instruction provides explicit teaching on how to interpret and apply feedback effectively, helping learners build metacognitive awareness and refine their strategies; (c) critical framing prompts learners to evaluate the source, quality, and implications of feedback, including AI-generated suggestions, within broader cultural, ideological, and ethical contexts (The New London Group, 1996); and (d) transformed practice encourages learners to integrate feedback meaningfully as they apply and adapt their learning across varied contexts, strengthening their ability to revise, transfer skills, and make independent decisions. Aligned with L2 and heritage language (HL) writing, LbD scaffolds learners in both monomodal and multimodal composition, positioning feedback as a key driver of reflection and development. Whether from instructors, peers, or AI tools, feedback becomes not just a corrective mechanism but a catalyst for critical thinking, problem solving, and autonomous writing.

When providing feedback on monomodal or multimodal texts, there is a need to remember that we can also provide multimodal feedback to our HL/L2 learners. As Mayer (2002) points out in his theoretical framework of multimedia learning theory, learners must integrate visual and verbal information. Grounded in cognitive psychology, this perspective holds that learners process input through two channels (i.e., oral and visual) with limited capacity and must actively construct meaning. When information is distributed across modes (e.g., pairing images or on-screen markup with spoken or written explanations), it can reduce unnecessary cognitive load and support deeper processing compared to single-mode presentation (Cavaleri et al., 2019). Mayer (2002) argues that multimedia learning is more effective than text-only approaches because it draws on two complementary processing channels in the human cognitive system, one for visual/pictorial information and another for auditory/verbal information. Each channel, Mayer (2002) continues, can handle only a limited amount of information at once, and learning involves actively coordinating cognitive processes across these channels. Accordingly, combining text and images supports the construction of complementary verbal and visual representations, and the connections between them, whereas text-only input tends to produce a verbal model whose integration with a visual one is limited.

Many of the studies that have considered multimodal feedback in L2 have compared monomodal written feedback in texts (e.g., comments in Microsoft Word documents or corrections in the text itself), audio text, and multimodal feedback using Screencast-O-Matic or another video platform to provide both visual and verbal feedback (Bakla, 2020; Elola & Oskoz, 2016, 2022). These studies provide mixed findings. Whereas Ducate and Arnold (2012) and Elola and Oskoz (2016) found no significant differences in terms of error correction between written feedback and screencast feedback, Cunningham (2019) reported that her learners conducted more successful revisions and made slightly more global changes after screencast feedback compared to those who received written feedback. Further, Imsa-ard and Barrot (2024) found no significant difference in terms of complexity when receiving multimodal technology-mediated feedback compared to peer feedback; however, learners' performance was significantly higher in accuracy and fluency.

For our purposes, following a LbD framework, the instructor provides multimodal feedback to the learners in their monomodal texts and infographics. The multimodal feedback provided can also be a follow-up to the comments that learners received from AI (see Figures 3-7).

4.3.1. Situated practice

Learners draft their individual infographics on Apollo 11 (date, crew, quote, sampling purpose, training, legacy). After learners receive AI feedback (see Tables 1 and 2), they mark the AI flags they trust (e.g., *people's beliefs*, *historical events*) and the ones they doubt. Learners use their own knowledge and the new knowledge provided by the instructor.

4.3.2. Overt instruction

The instructor gives a mini-lesson on how to read and use the AI feedback (see Section 3) in the infographic draft. Together, the instructor and learners identify the main patterns that need attention in the Apollo infographic:

- subject-verb and number agreement;
- verb tense consistency;
- cohesion;
- clear visual infographic structure.

Instead of asking students to correct everything at once, the instructor gives focused practice on just one or two of these points at a time. The instructor also provides multimodal feedback using screencasting so that learners can hear the feedback while the instructor provides feedback on specific linguistic and non-linguistic elements of the infographic. For example, the instructor can point out the subject in a sentence, highlight the verb, and ask learners to correct a clause for agreement. The instructor can also call learners' attention to the layout of the infographic, the title and the use of images (see Figures 8 and 9). This focused audio-visual feedback lowers the cognitive load and encourages learners to retrieve the rule themselves rather than simply receiving the answer. By the end, learners can explain both the language issues (grammar, tense, cohesion) and the non-linguistic issues (layout and clarity in a visual product).

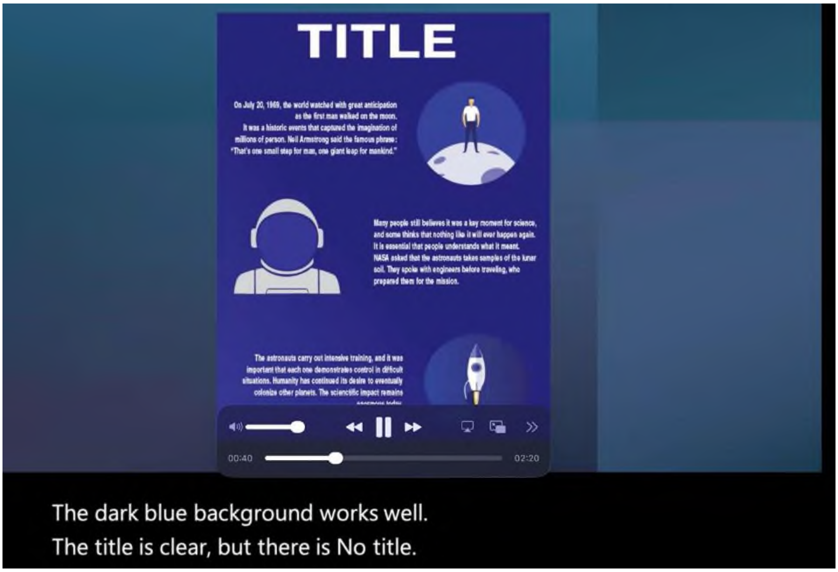

Figure 8 Example of audio-visual feedback regarding title

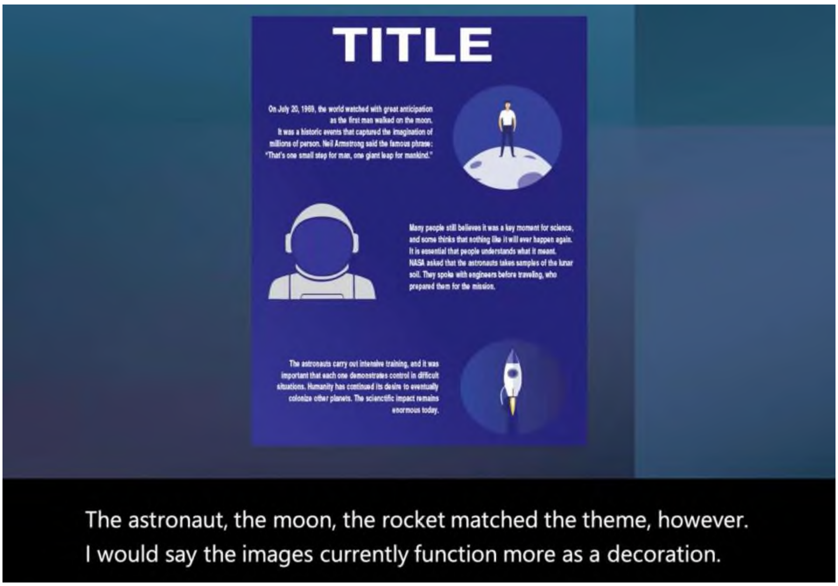

Figure 9 Example of audio-visual feedback regarding images

4.3.3. Critical framing

Learners review all suggestions (in our case from the instructor and AI) and sort them into three actions: keep, modify, or ignore. For each decision, they add one short reason that connects to the audience, the goal of the text, or how the words and visuals work together. The goal is that learners learn to accept or reject suggestions for good reasons instead of automatically doing whatever the tool or another person suggested. Learners also include, in writing, what they chose to keep from AI feedback and what they chose not to use and why.

4.3.4. Transformed practice

Learners create a revised version of their Apollo infographic that is easier to follow and better organized, not just "prettier." With the final version, they also turn in three short pieces: (1) a change log listing three specific changes they make and why (e.g., "We added a timeline so the reader can see the sequence of events"); (2) one new sentence where they apply a rule they learned (e.g., past vs. present tense); and (3) a short statement explaining which AI tool they use, what they use it for, and how they check it. This process allows the instructor to see whether learners can use their L2 appropriately and coordinate text, images, and layout for a real audience. In sum, the goal across this cycle of steps is for feedback to function as a tool for reflection, autonomy, and critical thinking: Learners notice and diagnose issues, apply targeted revisions, evaluate suggestions (including AI) against communicative aims, and produce redesigned texts that generalize beyond the Apollo task. Learners are able to apply their knowledge and get creative with the infographic. The final infographic can look something like the one depicted in Figure 10.

5. Conclusion

The current reconceptualization of feedback aligns with the growing consensus that no single theory can account for feedback in multimodal and AI-enabled environments. A comprehensive understanding requires complementary theoretical perspectives, integrating cognitive perspectives on attention and memory, sociocultural models of mediation and agency, and multiliteracies frameworks addressing design and semiotic orchestration. Following this view, feedback functions not merely as correction but as a distributed process of connection linking the cognitive, social, and technological dimensions of writing. As we continue integrating

AI-mediated feedback into our L2 practices, there is a need to address learners' accountability and responsibility as they use these tools ethically by, for instance, giving credit for images or media employed, making products accessible (e.g., using clear captions), and noticing when "standard" phrasing might erase the writer's own voice.

Figure 10 Example of revised infographic (Image created by ChatGPT)

There is a need for further research that aims to generate empirical evidence on the role of multimodal feedback in both monomodal and multimodal writing tasks and its impact on language development. To address the complexity of these practices, it is crucial to further examine complementary theoretical stances. For instance, such research could place perspectives on mediation and interaction in dialogue with post-humanistic accounts of distributed agency across human and technological agents and tools. We also need to examine AI-mediated feedback from an ecological perspective that foregrounds learner agency, equity, and the co-design of learning experiences. To fully benefit from the positive contributions of AI in the HL/L2 classroom, we must explore the affordances that AI may offer for feedback and consider how learners' characteristics, such as motivation, prior writing experience, and cognitive profiles, influence the use and effectiveness of AI-based monomodal and multimodal feedback. By conducting both one-time and longitudinal studies, HL/L2 researchers and instructors will better understand how AI feedback practices evolve over time and will identify potential biases, particularly concerning language variation. This agenda seeks to articulate principled, equitable, and pedagogically grounded approaches to multimodal feedback in contemporary language learning contexts.

In line with the aims and scope of research in L2 learning and teaching, this paper has emphasized how feedback practices, particularly those mediated by AI, may support L2 learning in instructional settings. By foregrounding the role of learners, instructors, and technologies in shaping feedback processes, we aim to contribute to ongoing discussions on how feedback can be designed, interpreted, and enacted to enhance L2 teaching and learning outcomes, which remain central to the field.

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