

Independent Writing in the Machine Age: The Draft–Interrogate–Reflect (DIR) Model of Human–AI Interaction in Second Language Writing

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ABSTRACT

The use of generative AI in composing and editing text poses a challenge for language educators. On the one hand, writing in a foreign language (FL) is cognitively demanding. In the process of composing texts, errors in FL grammar, punctuation, and syntax (FLG/FLP/FLS) become noticeable, and learners revise them. On the other hand, writing with the help of AI may override the cognitive load necessary for learners to develop their ability to identify and revise errors in FLG/FLP/FLS. Some educators have banned the use of AI for editing and composing text; others have integrated it into their teaching without giving a rational account of when and how the technology should be used. This article aims to bridge this gap. It proposes a synthesis of sociocultural theory, cognitive load theory, and the noticing and output hypothesis. Based on the integration, it identifies the offloading-noticing paradox. Offloading the cognitive load for text revision to AI frees the writer's working memory for structuring and other aspects of composing. However, relying on AI may hinder the writer from noticing aspects of FL text that need revision. The article provides a resolution to this paradox in the form of the Draft-Interrogate-Reflect (DIR) cycle and a curricular plan for implementing the DIR cycle for a period of six weeks. A validation agenda and six working hypotheses are provided. The article gives a reconceptualization of the role of the teacher in relation to the mediating function of AI for language learning.

Keywords: generative AI; second language writing; sociocultural theory; cognitive load theory; noticing hypothesis; learner autonomy

INTRODUCTION

The final months of 2022 brought widespread publication of large language models (LLMs) in conversation formats. This created a 'Wild West' frontier for second language (L2) writing instruction and research. Digital writing aids that corrected common errors in spelling and grammar have expanded to include tools that generate well-structured, fluent academic discourse (Kasneci et al., 2023; Kohnke et al., 2023). LLM-based tools have the potential to provide timely and actionable feedback to L2 learners and facilitate writing practice. However, they have the potential to widen the learning and attainment gap for L2 learners. As Barrot (2023) notes, these tools can serve an instructive role to a degree that teachers cannot, especially when juggling the needs of a large class. LLMs are poised to rapidly replace traditional methods for writing practice. This leads to the Sapir-Whorf hypothesis (Whorf, 2019) for L2 writing. If the goal is for L2 learners to write fluent academic discourse in the target language, should educators promote and support the use of AI writing assistance? What does L2 writing practice look like if supported by LLMs?

Empirical evidence addressing these questions is scarce; however, recent neuroscience studies contribute to the discourse. In a 2025 study, Kosmyrna and colleagues reported on a neuroimaging experiment in which participants, when aided by large language models, exhibited reduced brain activity, less sense of ownership of their essays, and found it difficult to recognize their own writing. Participants who wrote traditional essays exhibited better memory and recognition of essay contents. Survey data also indicate that frequent use of AI writing tools negatively impacts students' critical thinking (Gerlich, 2025). Prior research on the impact of automated written corrective feedback, or AWCFF, showed that learners tend to engage with feedback in varying degrees and that some learners tend to accept feedback without evaluating it (Koltovskaia, 2020; Ranalli, 2018).

Initiating various changes in learning and pedagogy is likely to continue. For example, Su (2023) demonstrates the use of ChatGPT for revision and post-writing reflection in the context of an argumentative writing class, and Tseng and Warschauer (2023) describe a five-level AI literacy framework. These and related works are important and relevant, but tend to focus on demonstrating the use of AI in teaching, and less so on articulating the rationale for the use of such integrated sequences of human and machine interaction from the lens of foreign language teaching and acquisition. Consequently, there is a paucity of resources to help answer the most critical questions concerning the balance between the use of AI and its impact on learners' writing and other related critical activities. This article will fill an existing research void by developing a context-sensitive theory of integrating responsibly deployed GenAI in L2 writing classrooms. More specifically, the article addresses the following:

RQ1. In what ways do integrating sociocultural, cognitive load, noticing, and output hypotheses frameworks help to analyze the impact of AI in L2 writing?

RQ2. Based on the preceding analysis, what is the suggested order of instruction, and in what ways can it be accomplished without the use of technology?

RQ3. What is the potential of this framework and theory to generate testable hypotheses?

The article presents three major innovations. First, it describes and defines the Offloading-Noticing paradox. In addition, it provides evidence to support that with respect to resolving the Offloading-Noticing paradox, sequence is of greater importance than a complete prohibition or unconstrained reliance on GenAI. Second, the article describes and defines GenAI in the role of a teacher-directed mediational tool. Last, the article describes and defines the Draft-Interrogate-Reflect (DIR) model. The article provides a detailed description of the DIR model and outlines a six-week implementation plan. The article provides numerous suggestions and proposes a research agenda. The article describes the negative consequences of reliance on GenAI and addresses positive changes that may occur to L2 writing as a result of use of the Draft-Interrogate-Reflect model. The article describes the implications of GenAI on teaching and the classroom. The article addresses the trade-offs and provides evidence to support the value of the research.

LITERATURE REVIEW

From Automated Writing Evaluation to Generative AI

Automated tools to support L2 writing have been developed and modified over the years. Examples include computerized spell and grammar checkers and writing evaluation tools (AWEs). The latter are computer programs that score essays and provide feedback. In their research, Stevenson and Phakiti (2014) examined computerized feedback and published a series of studies to determine the effects of this type of feedback on writing. Overall, the authors found limited and inconclusive evidence on the improvement of writing quality as a result of the use of this type of feedback. The authors concluded that revising a writing draft based on computerized feedback may not improve the quality of the writing.

Additionally, Ranalli (2018), in another study focusing on learners' engagement with AWEs, found substantial variability in learners' behavior and cognitive and emotional acceptance of suggestions provided by AWEs.

The author of the present article considers the main findings and conclusions of this line of research to indicate that if learners do not process feedback, they will not improve their writing abilities and skills. According to Kohnke et al. (2023) one major difference between Generative Artificial Intelligence (GenAI) and earlier assistive technologies is that GenAI can generate text like a human being and goes beyond suggesting changes or corrections. The second major difference is that GenAI can engage learners in conversation. Therefore, with respect to writing, GenAI can provide suggestions and justifications for changes, and can defend and explain feedback. Consequently, Kohnke et al. (2023), suggest that GenAI will change the concept of feedback in Assistive Technology.

Generative AI in L2 Writing: Opportunities and Threats

A range of opportunities and threats regarding Generative AI (GenAI) in L2 writing have already been described. Barrot (2023) describes, for example, how GenAI provides automatic feedback, provides examples of appropriate language, and possibly saves time. However, Barrot also describes possible negative consequences of the use of GenAI in L2 writing. These include, for example, a decrease in the motivation of the learners, negative effects on academic honesty, and the quality of the written work.

A possible solution to the negative effects of using GenAI in L2 writing described by Su et al. (2023) would be to use GenAI to write the first draft of the work, but to reflect on the work after it has been written. Based on the AI's suggestions, the work would then be revised. Kohnke et al. (2023) describe the use of GenAI in the classroom as a way to deepen the digital competence of both the students and the teachers. UNESCO (2023) provides recommendations to incorporate GenAI in the classroom, emphasizing that human beings should retain control over their environment. GenAI should be used to augment human rationality.

Cognitive Offloading and Dependency

Cognitive offloading occurs when a person uses their environment or bodily actions to reduce the cognitive load of a task (Risko & Gilbert, 2016). In some cases, offloading may be adaptive, but it may also lead to a loss of memory regarding the information that is offloaded and the skills required to perform the task. Recent research that involves the use of GenAI predicts that offloading may be adaptive but may affect a person's ability to engage in critical thinking. In addition, offloading may lead to a loss of control and ownership over a task. Research indicates that writing a document without the use of GenAI may be preferable to writing a document and then using GenAI to edit the document.

The Research Deficit

This review identified three main research gaps. First, most recommendations on the use of GenAI in L2 writing do not clarify the psycholinguistic and sociocultural mechanisms upon which they are based. Second, most recommendations do not address how the competing needs of learners to reduce their cognitive load and monitor their learning may be balanced. Third, most recommendations do not address how teaching and assessment practices may facilitate learners to develop the capacity to learn and perform certain tasks without the support of GenAI. The DIR model is intended to address these three research gaps.

Conceptual Approach

This article describes a conceptual framework and follows a synthesis of theories and construction of a model (Jaakkola, 2020). In theory synthesis, new insights regarding a focal phenomenon are gained through integration of fragmented bodies of theories; model construction gives shape to the integrated theories in a manner suitable for empirical testing. The focal phenomenon is the influence of GenAI-based writing assistants on the independent writing ability of L2 learners.

Three theoretical frames are provided. Of the three, the other two, namely, cognitive load and writing, are concerned with learners' acquisition of the activity of noticing and/or writing to close gaps in interlanguage. It is indicated that the design of AI writing assistants may address the gaps and facilitate noticing. The key

element for the validity of the model is, citing Whetten (1989), specification of the relationships among the constructs and the conditions (i.e., persons, time, place) where the relationships apply and where the model breaks down.

Theoretical Integration

Sociocultural Theory: AI as Mediation Artefact

With reference to sociocultural theory, more complex psychological functions emerge as a result of social interaction and are internalized (Vygotsky 1978; Lantolf and Thorne 2006). The ZPD is represented by the space between what a learner is capable of performing with assistance and what the learner is capable of performing independently (Vygotsky 1978).

In connection with scaffolding, it is important to note that the degree of assistance is gradually lessened as the learners' level of accomplishment increases (Wood, Bruner and Collins 1976). In the context of second language acquisition, Aljaafreh and Lantolf (1994) indicate that in order to be helpful, feedback must be appropriately graduated; that is, it must be implicit if the learner is capable of self-regulation and it must be withdrawn.

Although GenAI is often described using terms like "more knowledgeable other" (MKO), Vygotsky actually used the term "more knowledgeable peer." Further, GenAI suffers from a number of the same limitations as other artificial intelligence programs. An LLM has no way of understanding the developmental level of a user and, as a result, may provide incorrect but confident answers. Unlike a human, it will often provide a "finished" answer to a question where a hint would be more appropriate.

By default, GenAI provides non-contingent assistance and, as a result, may actually hinder development and inhibit the user's ability to think for themselves. This paper attempts to strike a balance by examining GenAI in the context of a mediational tool and considering how the technology can be integrated to promote optimal development. From a teaching perspective, it is important to consider how a given assistant technology integrates into a learning environment and controls when and how the technology assists. This is the foundation of the first element of the DIR model.

Cognitive Load Theory: What Should and Should not Be Offloaded

Cognitive load theory (CLT) focuses on the constraints of working memory, which is very limited when dealing with novel information, and the virtually unlimited capacity of long-term memory (Sweller, 1988; Sweller et al., 2019). CLT posits that a large portion of cognitive load during writing is devoted to planning. Moreover, writing requires intellectual effort to express ideas and standards in an articulate manner (Flower & Hayes, 1981).

This is particularly challenging for L2 writers who need to devote cognitive effort to express ideas using language structures (Kellogg, 2008). CLT describes three types of loads. While intrinsic load describes the interrelation among the components of the information to be learned, extraneous load refers to cognitive overload caused by deficiencies in instruction. In recent years, it has been proposed that germane load be conceptualized as a form of intrinsic load and, thus, cognitive effort devoted to dealing with it would be considered working memory load (Sweller, 2010; Sweller et al., 2019).

There are consequences for machine-assisted writing. Older interpretations of CLT might propose AI should remove all 'mechanical' tasks, thus releasing writers' time for more cognitively demanding tasks. More recent interpretations of CLT suggest that the linguistic work of formulating and correcting L2 utterances is an intrinsic part of language learners' work.

Thus, 'mechanical' work for language learners is the processing work required to construct L2 schemas. Based on CLT, what is extraneous in language learning should be removed. In other words, the work required for

language learners to manage their cognitive load by, for example, organizing the presentation or searching for information, should be taken over by the computer. According to CLT, the work done by the computer should be reduced, and the direction and depth of the guidance should be modified according to the improvement and change in the language learners' expertise.

Noticing and Output: Why Learners Must Stay in the Loop

The hypotheses of Swain (1985, 1995) and Schmidt (1990) both argue that the input becomes intake when learners notice language features. While Schmidt focused on input and intake, Swain emphasized output. Swain claimed that generating language prompts learners to process language in a deep and meaningful way. Swain identified three functions of output.

First, output has a 'noticing' function. By trying to produce language, learners become conscious of the language they do not know. In the case of output, learners also function at a 'hypothesis-testing' level, where learners make an effort to produce language and verify their hypotheses by relying on feedback. 'Metalinguistic' refers to language about language. Lastly, Swain claims that language has the function of 'reflecting' on language.

These functions are supported by research that focuses on corrective feedback and self-repair. Lyster and Ranta (1997) argue that learner uptake is higher when a teacher prompts a learner to identify language deficiencies as opposed to when a teacher tells the learner the correct answer. When using an AI writing tool, learners often write a first draft and then refer to the AI feedback to write subsequent drafts. If the AI produces the first and last draft, learners do not have the opportunity to notice the gap between their interlanguage and the language model.

The Offloading-Noticing Paradox and its Resolution

The tensions that emerge from integrating the three lenses describe the same paradox. Using CLT, complete AI assistance is viewed positively, freeing up cognitive resources. The noticing and output hypotheses argue that the cognitive work, or noticing, that AI facilitates is pivotal to the learning process. This work, therefore, should not be fully relieved by AI. Generally, the use of AI to facilitate learning in higher education should be considered with caution until it evolves to fully align to the requirements of sociocultural theory. Therefore, the use of AI in higher education to fully offload linguistic functions should be avoided, in consideration of the offloading-noticing paradox.

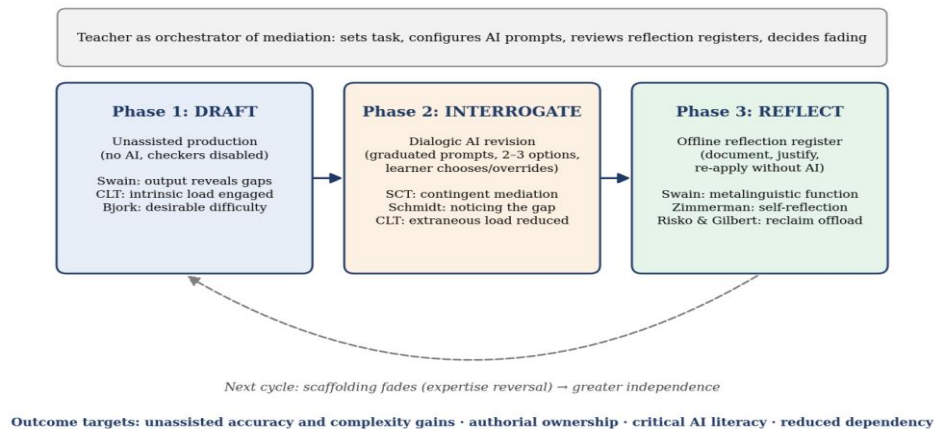
The paradox can be resolved by employing different structural strategies for the use of AI in writing, in which each phase would respond to one of the two lines of argument. Initially, students should be asked to generate unassisted writing, to create output with gaps (Swain 1995), thus increasing their cognitive load by means of a 'desirable' difficulty (Bjork 1994) that promotes retention.

AI writing assistants should be used in a second phase to provide different types of interactive and scaffolded assistance that require learners to decide and justify their choices (Aljaafreh & Lantolf 1994; Lyster & Ranta 1997). Third, learners use an offline phase to reclaim the processing they've offloaded and summarize the changes. They explain these changes to others and thus internalize the changes (Risko & Gilbert, 2016; Swain, 1995). Lastly, learners engage in self-reflection (Zimmerman, 2002). These elements form the basis of the Draft-Interrogate-Reflect model.

The Draft-Interrogate-Reflect (DIR) Model

The DIR model of L2 writing presents a series of steps and relies on the elements of theory and principle outlined above. Each step of the model addresses a key risk associated with the integration of AI in teaching and learning. The model is repeated throughout a teaching/learning unit and, where appropriate, teacher supervision of AI is removed. Teacher mediation determines the sequence of activities, adjusts and edits AI prompts, reviews reflection journals, and decides when to remove teacher support.

Figure 1. The Draft–Interrogate–Reflect (DIR) model of human–AI interaction in L2 writing



Note. CLT = cognitive load theory; SCT = sociocultural theory. Solid arrows show the within-task sequence; the dashed arrow shows the next cycle, in which AI scaffolding is reduced.

Phase 1: Draft (Unassisted Production)

This phase requires learners to create a complete first draft without the use of AI. Handwritten drafts are acceptable. Predictive text, as well as spelling and grammar suggestions, should be disabled on the computer. The main objective is to help learners write a complete first draft without AI and to capture a sample of learners' writing without automation. A byproduct of this phase is that it helps the learners recognize the gaps in their knowledge and resources (Swain, 1995) and focuses on improvement (Bjork, 1994). The phase also provides the instructor with the current level of each learner's writing without the instructor's guidance and/or correction. This is the case unless, of course, the instructor is testing the AI's capabilities. The AI cannot write what the learner already wrote.

Phase 2: Interrogate (Dialogic Engagement with AI Feedback)

AI use in this phase is more structured. In addition, a teacher's aide prompts students to use AI to revise their writing in a specific way. The phase's structure and the way prompts are offered reflect the scaffolding described by Aljaafreh and Lantolf (1994). Self-repair and self-correction are fostered. Reformulation is offered as a last resort.

Three aspects structure this phase: Graduated Prompting, Evaluative Choice, and Authorial Override.

Phase 3: Reflect (offline reflection register)

Finally, the AI is eliminated and removed from the context. The students are provided a copy of their original draft as well as the revised draft and are asked to complete a Reflection Register. In the Register, students are to explain each change and indicate if the change was made by the AI. Students are to indicate if the suggestion made by the AI was correct, and if not, why the suggestion was rejected. The explanation by students helps provide insight to the teacher as to what type of changes need to be taught to the AI. Finally, students complete a task to practice editing or creating a text like what was suggested or created by the AI. The suggested edits or text created by the AI is to be carried out without the help of the AI. This portion helps build students' ability to reflect and edit their own work, a skill known as self-regulated learning. As a side benefit, students are recapturing the processing that was previously handled by the AI. This has the added benefit of giving the teacher insight as to what changes were made by the students and the rationale by students for making the edits. This was captured in a digital format and can be printed by the teacher. The offline processing helps the teacher gain insight into student work as well as provide instructional feedback. The

teacher is also able to gain insight into what edits were made to the students' work. This helps with the integrity of the assignment.

Summary of Theoretical Anchoring

Table 1 summarises how each phase of the model is anchored in the theoretical integration and which risk of AI use it addresses.

Table 1. Theoretical anchoring of the DIR model

Phase	Theoretical anchor	Mechanism	Design principle	Risk mitigated
1. Draft	Output hypothesis (noticing function); CLT (intrinsic load); desirable difficulties	Learner experiences gaps in own interlanguage	No AI assistance before a complete draft exists	Substitution of learner production
2. Interrogate	SCT (graduated, contingent mediation); noticing hypothesis; corrective feedback research	Gap between draft and feedback becomes salient; learner must evaluate	Graduated prompts; 2–3 alternatives; learner choice and override	Passive acceptance of AI output
3. Reflect	Output hypothesis (metalinguistic function); self-regulated learning; cognitive offloading research	External assistance re-represented internally and re-applied	AI removed; documented, justified revisions; transfer task	Shallow processing; lack of retention
Across cycles	Expertise reversal effect; scaffolding	Assistance matched to developing competence	Progressive fading of AI support	Long-term dependency

Curricular implementation: a six-week blueprint

Table two shows a sample DIR unit over a 6-week writing program for argumentative writing. The full cycle is applied week by week to a different focus but with reduced amounts of support from AI, with the first and last week offering baseline and outcome measures without AI support. The blueprint is provided as an example and will need to be adapted to local syllabus, standards and time limitations.

Table 2. Illustrative six-week implementation of the DIR model

Week	Focus	Phase 1: Draft	Phase 2: Interrogate	Phase 3: Reflect	Evidence collected
1	Baseline	Unassisted argumentative essay under timed conditions	Not used	Learners set goals from teacher diagnostic feedback	Baseline essay (CAF measures; rubric score)
2	Word choice and academic vocabulary	Paragraph drafted unassisted	AI gives hints on imprecise words; offers 2–3 options with explanations	Register of lexical changes; new sentences using chosen items	Chat log; reflection register
3	Sentence structure and grammar	Paragraph drafted unassisted	AI indicates error type and location only; explicit rule	Register of grammatical changes; similar-sentence correction task	Chat log; register; transfer task

Week	Focus	Phase 1: Draft	Phase 2: Interrogate	Phase 3: Reflect	Evidence collected
			on request		
4	Coherence and paragraph organisation	Full essay drafted unassisted	AI asks questions about logic and links rather than rewriting	Learner annotates how organisation changed and why	Register; annotated drafts
5	Integrated revision with reduced support	Full essay drafted unassisted	Hints only; no alternative formulations	Comprehensive register; self-assessment against rubric	Chat log; register; self-assessment
6	Independent performance	Unassisted essay under the same conditions as Week 1	Not used	Reflection on progress and on AI use	Outcome essay; delayed post-test after 4–6 weeks

Note. CAF = complexity, accuracy, and fluency (Housen & Kuiken, 2009).

Implementation in Resource-Poor Settings

As with most educational technology research, the DIR model has not been developed with the conditions prevalent in most schools in the Global South in mind, notably, a lack of reliable broadband and one-to-one student-to-device ratios. The DIR model aims to keep its use of technology to a minimum. The key phases that consume the major part of class time in the DIR model do not need aided human interaction and can be implemented using pen and paper. Only one of the key phases needs assistance from artificial intelligence. This phase can be implemented in several ways. For example, the teacher can ask the AI to suggest changes to a student's response, which the student can implement, or the teacher can implement the suggestion and project it to the class for discussion. As the teacher does not know the student's access to the Internet, she should not evaluate the student based on the suggestions implemented. To test the AI, the teacher should use one that can be accessed for free. The DIR model can be used to engage students to interact with any conversational artificial intelligence that the school allows students to use.

Propositions and Validation Agenda

Propositions

The integrated theory from this study allows for the formulation of the following propositions that lend themselves to verification through scientific research.

P1 (Sequencing). Writing accuracy in unassisted post-tests will improve for L2 learners who write an initial unassisted draft as compared to learners who write with AI feedback during all, or part of, the writing process.

P2 (Graduated Prompting): Feedback from the AI will be more effectively used by the learner when the AI does not provide the corrected answer. Rather, the AI should use graduated prompts to help the student reach the correct answer.

P3 (Evaluative Choice): Using an AI to give a student a series of possible answer choices will cause the student to "notice" more than if the AI told the student the correct answer.

P4 (Reflection): Learnings from reflective writing regarding the justification of rules and changes will help better predict if a student is able to answer a certain writing prompt correctly.

P5 (Fading): As a student becomes more proficient in writing, and therefore less reliant on AI, AI writing

assistance will become less beneficial and less warranted.

P6 (Ownership and Dependency): Compared to other students, those who participated in the DIR cycle will report feeling more able to write on their own and will report less reliance on AI to assist them while writing.

Validation agenda

Propositions can be evaluated through a quasi-experimental design whereby three different groups (i.e., exposure conditions) are formed by allocating intact classes to (a) the DIR cycle condition, (b) the unstructured AI use condition, and (c) the no-AI condition. All groups will be administered an unaided pre-test. Following this, all groups will be administered a post-test, and several weeks later, a second post-test will be conducted with each group interacting with an AI in the absence of teacher direction or student interaction. For this validation study, process data will be collected as AI chat logs will be analyzed for student responses to AI suggestions and student reflections, and will be coded based on Schmidt's (1990) 'depth of noticing.' To help understand why differences may exist among the three groups, students may be further asked to participate in 'think aloud' activities. As an additional measure to assess student perceptions of reliance on AI, student interviews will also be conducted.

Table 3. Propositions and indicative measures for empirical validation

Proposition	Comparison	Indicative measures
P1 Sequencing	Draft-first vs. AI-first	Accuracy (error-free clauses) on delayed unassisted post-test
P2 Graduated prompting	Graduated prompts vs. direct correction	Proportion of self-repair and uptake in chat logs
P3 Evaluative choice	Multiple options with choice vs. single suggestion	Frequency of documented noticing in registers and think-alouds
P4 Reflection	Within DIR group	Register depth score as predictor of accuracy gain
P5 Fading	Faded vs. constant AI support; proficiency as moderator	Post-test gains by baseline proficiency level
P6 Ownership	DIR vs. unstructured AI use	Ownership and reliance questionnaire; interviews

DISCUSSION

Theoretical contributions

The DIR model describes the offloading–noticing paradox, provides a theory to address this paradox in relation to established theories in SLA and learning, and illustrates how both the pro and anti-GenAI positions are inadequate. The model describes this paradox as arising from contradictory implications of the communicative and the noticing and output hypotheses. Further, the model describes how the paradox can be ameliorated by structuring and sequencing in the classroom, which can help reconcile conflicting perspectives about GenAI in language teaching. Finally, the model provides a sociocultural theory framework to interpret AI and helps ascertain when and how AI can be gradual and interactive, which is critical for the teacher to design classroom tasks and activities. Therefore, the model identifies the developmental potential and impact of AI in the classroom and enables a theory-informed perspective about how to adapt and design integrative learning activities and tasks. The model also accounts for the contradictions described by Warschauer et al. (2023) in different ways. Regarding the with-or-without contradiction, the condition is incorporated in all cycles of the model; that is, students write without the assistance of AI, then with it, and then without it, again. With regard to the imitation contradiction, students are required to go beyond imitating the AI response by interpreting and justifying it in their own words. The model, together with teachers' professional judgment and

orchestration, incorporates the use of prompting and exemplification to give less proficient learners feedback that makes it useful and interpretable. Ultimately, this is an empirical question, described in point P5.

Implications for Teachers and Curriculum Developers

The model places a different emphasis on teachers. Instead of spending time controlling students' usage of AI, teachers are now instructed to consider different ways to integrate AI in the classroom. Based on the model, teachers have three main responsibilities. First, teachers continue to incorporate unassisted writing in the classroom. Second, teachers must create AI prompts in which the feedback provided by the AI to the students is graded, instead of providing a complete response. Third, teachers can change the types of evidence they assess. Previously, teachers assessed the finished product. However, with the model, teachers can assess process evidence and integrate other types of evidence, including AI prompts, reflection, or other auxiliary aids. In addition, teachers can incorporate the six-week model described by the authors to create their own teaching units based on their local context.

Academic Integrity and Learner Agency

Responding to academic integrity concerns typically involves monitoring students and assuming students are behaving suspiciously, which is neither effective nor respectful to students. The DIR model provides transparency during the process. Because each cycle results in an AI-generated draft, illustrates the interaction, and describes edits, the process is fully traceable. More importantly, the model enables students to decide whether to trust and adopt suggestions. By doing so, the model provides students the opportunity to critically analyze suggestions and evaluate AI-generated content. This method fosters students' critical AI literacy, endorsed by experts (Tseng & Warschauer, 2023; UNESCO, 2023), and their authorial agency (Kosmyna et al., 2025).

Equity in resource-constrained situations

To reduce barrier concerns, this model allows educators to moderate and, simultaneously, limit students' access to AI. Models of educational technology that presume students have individual, constant, and unrestricted access to the Internet can widen equity gaps between higher- and lower-income nations. This model attempts to function within the constraints of the digital divide.

LIMITATIONS AND BOUNDARY CONDITIONS

The authors identify several limitations in their paper. First, the authors acknowledge the DIR model is theoretical and has not been formally created or tested. The authors suggest further research in order to validate their model. Second, the authors say the model is only beneficial to intermediate level learners of English as a Second Language at the secondary and post-secondary levels. Beginner level students may require more scaffolding than what is suggested in the model and more advanced students may not benefit from what is suggested in the model (Kalyuga et al., 2003). Third, the model relies on the feedback AI gives and may be incorrect. The model suggests that dealing with the feedback would be beneficial to students. The authors suggest that further validation of the model through research may help support the model. Fourth, the use of reflection registers may be time-consuming for students and may increase the workload of teachers. However, using peer reviews to evaluate reflection registers may reduce the time each teacher would need to spend evaluating each reflection register. The model suggests that in order to give students the appropriate assistance, the model would need to constantly be reviewed and revised based on changes made to the goals and strategies of the AI. The model suggests that the benefits of the model may be limited to assisting students of English as a Second Language in writing argumentative essays.

CONCLUSION

Instead of encouraging learners to internalize language production, generative AI allows L2 learners to have fluent and accurate written communication. The focus of this article is not to determine if learners should

utilize AI in class. The focus is to determine in what ways and in what sequences learners should utilize AI. To do this, the author used sociocultural theory and cognitive load theory to explain the offloading-noticing paradox. In addition, the author provides the Draft-Interrogate-Reflect model to resolve the paradox. This model is innovative in that it maintains unassisted language production, manipulates generative AI to support language evaluation, and eliminates generative AI to enable learners to reflect on and internalize what they have learned. The model describes a writing process and provides six statements that can be verified. In addition, the author notes the model is technology- and computationally resource-intensive and provides a process for teachers to integrate generative AI in language teaching.

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