Using AI to Support Structured Literacy

Aligning Tools with How Students Learn

International DYSLEXIA Association®

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EXECUTIVE SUMMARY

As artificial intelligence (AI) tools rapidly enter classrooms, educators and developers face a critical challenge: ensuring these technologies align with what we know about human learning, particularly students with reading difficulties. This brief provides a science-informed framework for evaluating how AI can support Structured Literacy instruction without displacing the expertise of teachers or undermining effective instructional design.

Drawing from contemporary research in cognitive science, linguistics, and educational psychology, the brief outlines how human learning is driven by multiple memory systems (i.e., explicit and implicit) that operate on different timelines and benefit from distinct forms of instruction and practice. Structured Literacy, when implemented with fidelity, engages both systems across phases of learning by building declarative knowledge during acquisition, promoting automaticity during fluency, and supporting flexible transfer during generalization and adaptation. However, many classrooms fail to provide the sustained, feedback-rich practice required to consolidate learning and ensure transfer, particularly for students with dyslexia and related difficulties with reading and writing.

AI tools hold potential as amplifiers of well-designed learning environments that foster structured practice, just-in-time feedback, and individualized pacing. The brief is grounded in the Expanded Instructional Hierarchy, which maps instructional phases to underlying memory systems and learning mechanisms. This model is a lens to evaluate AI applications' timing, purpose, and instructional alignment to Structured Literacy.

Practical recommendations are offered for educators, developers, and policymakers, protecting cognitive demand, supporting student effort, and maintaining instructional fidelity. Ultimately, the brief proposes that AI must be judged not only by how well it works as an intelligent agent mimicking human language and cognition, but by how well it reinforces rather than dilutes the science of reading and the science of learning. A six-question implementation checklist is included at the end to help educators and decision-makers apply these principles in practice.

PURPOSE AND FRAMING

As AI tools accelerate into classrooms, a central challenge has emerged: ensuring that they reinforce, rather than dilute, what we know about how students learn to read and write, especially for those most at risk. What role should AI play in literacy instruction, especially for students who need the most support? How can we ensure that AI strengthens instruction rather than shortcuts learning? What makes an AI tool instructionally sound, and how do we evaluate its impact based on how it shapes engagement, learning, and transfer? These questions are particularly urgent in Structured Literacy settings, where fidelity to explicit, systematic instruction is essential to ensuring access to literacy for all learners.

This brief offers guidance for integrating AI into Structured Literacy in ways that support how students learn to read and write. It adopts the Expanded Instructional Hierarchy (Odegard & Gierka, 2025) as a framework for mapping AI's role to the demands of each phase of learning. It also highlights how human memory systems help define what makes instruction effective.

At a practical level, this brief is intended to (1) offer clear criteria for evaluating AI tools based on how students learn, (2) help educators and developers apply the Expanded Instructional Hierarchy to technology integration, and (3) ensure that students with or at risk for reading difficulties are not further hindered by misaligned innovation.

More broadly, this brief aims to reframe how we think about AI in education. Instead of emphasizing efficiency or novelty, it calls for tools to be judged by how well they align with how students learn. It is written to help parents, educators, developers, and decision-makers speak a shared language about effective instruction. In a moment of rapid technological change, clarity and alignment matter.

The brief is grounded in a core principle:

AI tools should be evaluated not by their technical features but by how well they support authentic learning, sustained practice, and transferable skill development.

This principle is especially important for students with or at risk for reading difficulties. Like all tools, AI can be helpful or harmful depending on when, how, and why it is used.

CLARIFYING TERMS

Before exploring the opportunities and risks of using AI in Structured Literacy settings, we define a few core terms as they are used in this brief.

Structured Literacy refers to an instructional approach that is explicit, systematic, and cumulative (IDA, 2014). It emphasizes the linguistic structures of spoken and written language, including phonology, orthography, morphology, syntax, and semantics, and is grounded in decades of research on how children learn to read. Structured Literacy instruction is responsive to developmental needs and is especially critical for students with dyslexia and other learning difficulties.

The **Science of Reading** refers to a multidisciplinary body of research that examines how children learn to read, why some struggle, and which instructional practices are most effective. It draws from fields such as cognitive psychology, neuroscience, linguistics, and education to inform evidence-based approaches to reading instruction with a particular focus on phonology, orthography, word recognition, language comprehension, and fluency.

The **Science of Learning** encompasses research on how humans acquire, process, retain, and apply knowledge. It integrates findings from cognitive science, neuroscience, psychology, and education to explain the mental processes underlying learning and memory. This research informs the design of instruction, emphasizing how different systems (e.g., implicit and explicit memory) contribute to skill development and knowledge transfer over time.

The **Instructional Hierarchy** refers to a phase-based model of learning developed by Haring and colleagues (1978) that describes how skills are acquired, refined, and transferred. This brief adopts an expanded version of this model to clarify instructional goals across the instructional phases and provide a practical framework for evaluating AI integration (i.e., the Expanded Instructional Hierarchy; Odegard & Gierka, 2025).

Explicit Memory (i.e., declarative memory) is a form of long-term memory that is consciously accessible and depends on attention. It allows individuals to recall facts, concepts, and past experiences with a sense of awareness or subjective remembering. Declarative memory includes semantic memory (knowledge of facts and concepts) and episodic memory (recollection of specific events and experiences).

Semantic Memory is a type of declarative memory that stores general knowledge, facts, concepts, and language-based information, such as the meanings of words, phonics rules, or grammatical structures. It is critical for Structured Literacy instruction and is supported by explicit, direct instruction.

Episodic Memory is a type of declarative memory that encodes personal experiences and contextual details (e.g., when, where, how something was learned). Episodic memory supports learning by linking new information to contexts.

Implicit Memory is a system of unconscious learning (e.g., procedural learning, statistical learning) that develops through repeated experience and practice. Implicit memory helps build automaticity and fluency by tuning attention, detecting patterns, and consolidating routines without requiring conscious recall.

Transfer refers to applying learned knowledge or skills in new or unfamiliar contexts. It is a key goal of deep learning.

Artificial Intelligence refers to computer systems that can perform tasks that typically require human intelligence, such as generating text, recognizing speech, or making predictions. This brief focuses on two broad types of AI tools: intelligent tutoring systems and large language models.

Intelligent Tutoring Systems (ITS) are structured programs that guide students through content using rule-based feedback, often with a narrow instructional focus.

Large Language Models (LLMs) are AI systems (e.g., ChatGPT) trained on massive amounts of text data to generate human-like language and provide real-time responses to user input.

WHY NOW?

The integration of AI into classrooms is accelerating. While Structured Literacy is grounded in decades of research on human learning, spanning cognitive science, neuroscience, linguistics, and education, active engagement by tech firms with educators, teacher unions, and other stakeholders raises concerns. These efforts to integrate AI in classroom settings risk further commodifying the educational setting, rather than prioritizing the educators shaping future generations of informed global citizens (O'Donnell, 2025). AI tools have outpaced our collective understanding of how they interact with memory systems, cognitive load, and transfer. We have seen the emergence of large language models (e.g., ChatGPT) and the enthusiastic appeals to integrate them into education in just a few years. In truth, many educators have not been equipped with a deep understanding of how learning unfolds across systems or instructional phases. AI integration must be grounded in both the science of reading and the science of learning.

Many current tools offer promise but lack alignment with instructional principles that support skill development and long-term learning. Without thoughtful design and guidance, AI systems risk flattening instruction, applying the same surface-level interface across all phases of learning, regardless of student need. To prevent this flattening, we need clear, phase-specific guidelines to ensure AI tools support, rather than undermine, effective teaching. Aligning AI with the distinct goals of Structured Literacy can safeguard instructional fidelity, engagement, and meaningful learning, especially for students with dyslexia and other reading difficulties. However, guidance alone is not enough. Before we can guide the future of AI-enhanced instruction, we must first understand where we are in its developmental trajectory. How did we get here, and what is emerging now?

Many current tools offer promise but lack alignment with instructional principles that support skill development and long-term learning.

Emerging AI: *From Intelligent Tutoring Systems to Generative Tools*

As we explore AI's role in education, a grounding question arises:

What are the emerging innovations in AI, and how did we get here?

The idea that computers could support individualized instruction and feedback one day is not new. In the 1970s, early intelligent tutoring systems (ITS) were designed to emulate human tutors by guiding students through content, identifying errors, and offering feedback based on rule-based models (Nye et al., 2014). These systems proved effective in structured domains like math and science but struggled with open-ended tasks and natural dialogue. A notable advancement came with AutoTutor, which incorporated basic natural language processing to evaluate student responses and allowed learners to interact with a virtual tutor using typed or spoken input (Grasser et al., 2007). These systems focused on helping students acquire factual knowledge through tightly structured instructional frames.

Today's AI tools are more powerful and flexible. Generative AI systems, built on large language models (LLMs) like ChatGPT, CoPilot, and Claude, can produce new text, simulate conversations, and scaffold complex tasks in real time. Unlike earlier ITS, LLMs are not limited to pre-programmed scripts. Instead, they detect patterns across massive datasets of written language and generate responses dynamically based on prior input and context. This flexibility allows them to support a broader range of interactions and introduces new challenges, particularly around alignment with instructional goals, accuracy, and appropriateness.

Notably, LLMs are only one form of AI. Today's education technologies often combine multiple forms of artificial intelligence. Some tools use adaptive algorithms to adjust pacing, difficulty, or content selection based on learner performance. Others use synthetic speech and speech recognition to engage students in real-time spoken interaction. These embedded forms of AI are now commonplace in reading platforms, fluency tutors, and feedback engines. What links them is not their technical architecture, but their function. Each is designed to interact with students in ways that mimic or extend human instructional support.

This is where natural language becomes so powerful. Language is the primary medium of instruction, and the ability to interact with educational tools through speaking, listening, reading, and writing changes the interface between students and content. AI is no longer running in the background making recommendations about a teacher or student's next steps. It is becoming an active participant in instruction engaging more directly with students using natural language in ways that are analogous to teachers. Moreover, with this shift comes a critical responsibility. Primarily, to ensure that AI's instructional role is aligned with what we know about how students learn.

AI AND LITERACY: A LONGER STORY

Long before generative AI, in the form of Large Language Models, arrived, researchers have used artificial intelligence to support literacy learning for decades.

For example, AutoTutor for Adult Reading Comprehension (AT-ARC), developed at the University of Memphis, is a web-based intelligent tutoring system that helps adults build reading comprehension and digital literacy skills. The program uses conversational "trialogues" among two computer agents and the learner to model strategies, provide feedback, and adapt instruction in real time. Studies show that when used alongside classroom instruction, AT-ARC improves adults' comprehension outcomes and digital-navigation skills. Its design principles (adaptive feedback, accessible interface, and explicit modeling) anticipate many of the same learning mechanisms now discussed in connection with large language models.

Takeaway

AI-based tools are not new to literacy education. The current generation of generative systems represents an evolution of earlier intelligent tutoring approaches aimed at reinforcing explicit instruction, feedback, and adaptive practice.

HOW WE LEARN

A Systems View of Human Learning and Memory

Human learning is not a single process. It is the product of multiple learning and memory systems, each with distinct representations, constraints, and timelines. Explicit memory (semantic and episodic memory), which is also known as declarative memory, support the conscious learning of facts, explicitly stated rules, and structured knowledge, such as how letters map to sounds or how morphemes combine to form words (Squire, 2004; Squire & Dede, 2015). These systems are the foundation of accuracy and conceptual understanding, allowing learners to verbalize and intentionally apply what they know. However, they are also fragile and capacity-limited. Explicit learning requires effortful attention and rehearsal, and the information it encodes fades quickly without deliberate retrieval and review (Norman & O'Reilly, 2003; Schacter & Tulving, 1994; Tulving, 1985).In classroom contexts, these constraints make explicit instruction powerful—but at a cost. It can produce rapid initial gains, yet it requires sustained retrieval practice to prevent forgetting and cognitive overload.

In contrast, implicit memory operates below conscious awareness. Through repeated exposure, practice, and feedback, it allows learners to detect regularities, consolidate routines, and perform with fluency. Implicit learning unfolds gradually and is less flexible in the moment, but the knowledge it encodes becomes more durable, efficient, and context-independent over time (Romberg & Saffran, 2010; Saffran et al., 2008; Squire & Dede, 2015). Consider orthographic mapping as an example. When students first learn that *"ph"* represents */f/*, this association is explicit and fragile. They must consciously recall the rule each time they encounter a new word. With repeated, accurate encounters and immediate feedback during reading and spelling, the mapping becomes automatic. The learner no longer consciously retrieves the rule. Instead, the pattern is implicitly recognized and applied to new words. This shift from explicit effort to implicit fluency is what enables skilled reading. The same mechanism supports other forms of proceduralized knowledge, such as fluent handwriting, syntax use, or activation of meaning from morphemes and entire words.

Each system therefore carries complementary strengths and constraints. Explicit memory allows for rapid acquisition, flexible reasoning, and metacognitive reflection, but is resource-limited and vulnerable to forgetting. Implicit memory builds efficiency, stability, and generalization, but requires extensive, variable practice and provides little conscious access to the underlying rules. Effective instruction must leverage both scaffolding explicit understanding while providing repeated, feedback-rich opportunities for implicit consolidation and transfer.

While Structured Literacy aligns with both systems conceptually, many students do not receive sufficient opportunities to engage with them in practice. In under-resourced classrooms, students may be taught critical knowledge (e.g., phonics patterns or word structures) but often lack the structured, cumulative practice and responsive feedback needed to consolidate it. This implementation gap disproportionately affects students with reading difficulties (Kent et al., 2012; Vaughn & Wanzek, 2014).

AI may offer a meaningful contribution by strengthening the explicit system and supporting the gradual consolidation of implicit learning. It can provide retrieval prompts and metacognitive scaffolds that cue students to apply specific strategies when reading, spelling, comprehending,

Figure 1. The Expanded Instructional Hierarchy

Instructional Phase	Learning Goal	Learning Processes	Role of Teacher	Role of AI	Risks/Design Considerations
Acquisition	Build accuracy and declarative knowledge	Effortful encoding, attention, semantic/episodic memory, retrieval practice	Provide explicit instruction, guide attention, model strategies, scaffold retrieval	Deliver structured prompts, corrective feedback, retrieval practice, spaced repetition	May promote passive learning; risk of confabulation or drift if not tightly aligned with scope and sequence
Fluency	Develop automaticity of learned skills and more automatic use of strategies	Procedural consolidation, implicit tuning, perceptual learning, rapid retrieval	Structure cumulative practice, monitor pacing, provide feedback, reinforce accuracy	Provide repeated, adaptive practice with real-time feedback; reinforce accuracy	Risk of superficial mastery; inadequate alignment to instructional sequence can create overload or confusion
Generalization & Adaptation	Promote flexible transfer and application	Analogical reasoning, metacognition, inferencing, cross-context integration	Design novel tasks, prompt transfer, scaffold problem solving, encourage autonomy	Generate varied examples, support interdisciplinary tasks, guide strategy reflection	Risk of over-scaffolding or “metacognitive laziness”; students may disengage from deep reasoning if over-reliant on AI

Note. Figure 1 provides a visual map of how instructional phases correspond to distinct learning mechanisms and memory systems, grounding AI integration in the realities of cognitive development.

or writing by helping them recognize when and how to use explicitly taught knowledge. For example, when a student encounters an unfamiliar word such as *"unknowingly"*, an AI system could prompt, *"Try peeling off any prefixes or suffixes. What base word do you see?"* (e.g., identifying *un-*, *-ing*, or *-ly*). As the student continues reading, the system might support comprehension monitoring by prompting attention to text features and structure. Such as, *"Notice how this paragraph introduces a new event. How does that fit the structure of a narrative?"* or by asking an inference-focused question such as, *"Is the author suggesting something that isn't stated directly?"* These dynamic cues help students effortfully activate and apply explicit knowledge while reading and writing.

The goal is for what begins as slow, effortful application of a strategy to evolve into fluent, context-independent performance.

AI can also amplify structured practice opportunities that reinforce implicit learning by delivering timely, individualized feedback and sufficient repetition for routines to become automatic. Through feedback-rich, distributed practice, knowledge that begins as slow and effortful becomes fluent and transferable across contexts. By supporting both retrieval and automaticity, AI can help orchestrate the complementary strengths of explicit and implicit learning to foster durable, generalized literacy skills. This phase-specific alignment is captured in the Expanded Instructional Hierarchy, which maps instructional goals onto underlying learning mechanisms and memory systems (Odegard & Gierka, 2025).

In the acquisition phase, students use explicit memory systems (i.e., semantic and episodic memory) through effortful encoding (i.e., the act of storing information in memory), attention, and retrieval practice. The instructional goal is to build accurate, declarative knowledge through explicit teaching and structured prompts. In the fluency phase, declarative knowledge must be consolidated into implicit and procedural memory, enabling faster, more automatic responses. This consolidation into procedural memory requires sustained, cumulative practice that supports perceptual learning, and rapid retrieval.

Finally, the generalization and adaptation phase demands coordination across learning systems. Learners must flexibly apply knowledge in new contexts using analogical reasoning, metacognition, and cross-situational integration, drawing simultaneously on explicit awareness and implicit pattern recognition. Each system contributes differently and operates under distinct constraints. The explicit system, which supports conscious rule learning and verbalizable knowledge, is highly context dependent. What is learned through explicit instruction often requires deliberate recall and environmental cues to be activated. The implicit system, in contrast, encodes statistical regularities through repeated exposure and practice, enabling transfer without conscious effort but only after sufficient repetition and variability.

Consider a student who learns to decode multisyllabic words or recognize morphemic patterns during a structured literacy intervention. Within that setting, the student reads accurately because the task structure, pacing, and scaffolds provided by the teacher and context cue explicit strategies. Yet in a history or science class, where texts are longer, vocabulary more abstract, and teacher prompts less directive, those same decoding strategies may not surface spontaneously. The knowledge exists but remains tied to the context in which it was learned. This reflects a constraint of the explicit learning system: it depends on context-dependent retrieval cues and conscious effort, making transfer less automatic.

Optimally, we want students to apply what they have learned flexibly across contexts. This can be supported by intentionally designing retrieval-based practice that prompts effortful recall of skills in new situations and by embedding varied applications that require learners to integrate knowledge across domains. For instance, after students learn prefixes and suffixes in a structured lesson, a teacher might prompt them a week later to spot and define those same patterns in a science passage or during spelling practice. That effortful recall in a new setting strengthens retrieval and helps the skill migrate from conscious rule use to automatic application.

Over time, distributed and diverse practice allows skills to consolidate within the implicit system, reducing context dependency and promoting automatic, generalized use. The goal is for what begins as slow, effortful application of a strategy to evolve into fluent, context-independent performance—a shift made possible only when both systems are engaged and their constraints are thoughtfully addressed in instruction.

Each phase poses distinct instructional demands and risks, as outlined in Figure 1. Without sufficient opportunities for repeated practice and varied application, learning may remain shallow, inflexible, or disconnected. AI tools must therefore be evaluated on what they deliver and whether they align with these phase-specific learning processes and memory systems. Effective AI use amplifies structured instruction, practice, and feedback, helping ensure that what students learn is retained, automatized, and applied. AI promises to foster the full potential of Structured Literacy. When Structured Literacy is implemented without sufficient attention to practice, feedback, and memory consolidation, its core principles remain theoretical rather than transformative.

INTEGRATING AI WITHIN THE PHASES OF THE INSTRUCTIONAL HIERARCHY

The Expanded Instructional Hierarchy offers a phase-based model that aligns Structured Literacy instruction with how learning unfolds over time. Its phases (i.e., acquisition, fluency, generalization/adaptation) provide a practical framework for evaluating how well a tool supports student learning. Each phase involves distinct cognitive demands and instructional needs. While AI can support instruction across these phases, it must be carefully aligned with the purpose and sequence of learning. Tools that are poorly timed, overly relied upon, or misaligned with classroom instruction may undermine long-term literacy outcomes. AI should extend, not replace, intentional and responsive teaching by highly qualified educators. The following section outlines how AI can be used strategically at each phase of instruction, along with potential risks that must be addressed.

ACQUISITION PHASE

Learning Goal: *Build accuracy and declarative knowledge.*

This initial phase focuses on helping students build accurate, declarative knowledge. Through explicit modeling and guided practice, students learn what to do and how to do it. AI can support this process by providing scaffolds and prompts that help students recall and apply what has been explicitly taught, such as highlighting key graphemes, cueing segmentation, or prompting a decoding step. In addition, AI tools can offer structured opportunities for review and real-time corrective feedback that reinforce connections among phoneme–grapheme correspondences, vocabulary meanings, and spelling patterns.

Effective acquisition requires helping students recognize when and how to apply the effortful strategies they are learning to read, spell, comprehend, and write accurately. When students struggle to retrieve or apply what they know, AI can provide responsive prompts and scaffolds that remind them of the relevant strategy, offer graduated hints, or model a step so that difficulty becomes productive rather than discouraging. It also requires structured practice spaced over time to strengthen memory traces and reduce forgetting. For example, after introducing a vowel team on Monday, a teacher might have students revisit that pattern later in the week through short reading with decodable texts and spelling activities that integrate them into new word lists, connected text, or dictation alongside previously learned syllable types. This distributed practice invites retrieval and application rather than re-teaching to develop accuracy. Some tools embed spacing (the deliberate scheduling of review opportunities after optimal intervals) and interleaving (mixing related but distinct skills or concepts within practice) to improve retention and promote flexible retrieval.

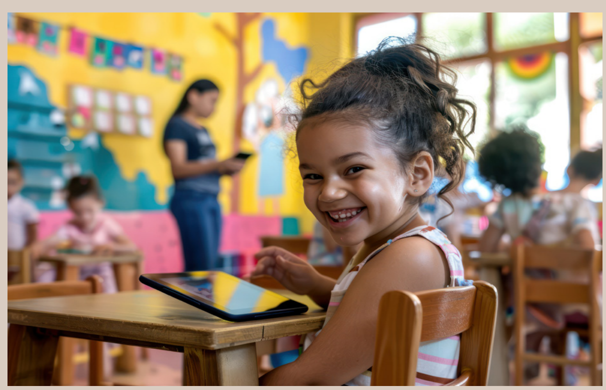
AI systems are uniquely positioned to personalize these schedules by analyzing individual performance data to generate optimal spacing and interleaving patterns for each learner. This adaptive sequencing can help ensure that practice remains targeted, efficient, and aligned with instructional goals. However, not all systems are equally reliable. Tools that stray from core instructional objectives, or lack alignment with classroom lessons may create confusion or introduce errors, particularly for students with diverse speech patterns or limited background knowledge.

TEACHING **TIP**

Choose tools that mirror the structure of classroom instruction. AI should reinforce what is being taught and always clarify the learning objective. There must be alignment between the AI learning experiences and the curriculum's scope and sequence.

LEARNING **VIGNETTE**

A first-grade student is introduced to the grapheme ***"igh"*** as representing the */ī/* sound. The teacher explicitly models its use in words like ***"light"*** and ***"night,"*** and the teacher guides student practice to read and spell those words. Later, a well-aligned AI tool offers a practice set that revisits this grapheme in new words, phrases, and sentences.



The tool provides immediate feedback and interleaves practice with previously taught concepts, spacing sessions across days to promote durable learning. Because the timing supports retrieval rather than passive recognition, the student begins to consolidate this orthographic mapping into long-term memory.

FLUENCY PHASE

Learning Goal: *Develop automaticity of learning skills and more automatic use of strategies.*

In this phase, students move from effortful accuracy to automatic, efficient performance. Building fluency requires cumulative and responsive instruction that strengthens procedural memory through repeated application. Decodable texts continue to play an important role, supporting accuracy by reinforcing taught grapheme–phoneme correspondences. AI can assist by generating decodable passages that align precisely with classroom instruction, tracking student progress in real time, and individualizing practice to help students consolidate what they have learned.

Fluency development also requires stretch texts that move students beyond purely decodable materials. Once foundational accuracy is established, students benefit from engaging with connected texts that include more complex syntax, varied vocabulary, and richer ideas while maintaining alignment with previously taught patterns. The optimal balance between decodable and stretch texts depends on the learner. Some students need continued decoding support and frequent review of recently taught correspondences, while others may advance more quickly to connected reading that promotes comprehension, expression, and motivation. AI can help calibrate this balance by generating texts tailored to each student's demonstrated proficiency and growth trajectory.

Some tools prompt rereading, adjust difficulty based on performance, or highlight areas for improvement. These supports can be powerful when coordinated with classroom instruction. However, tools that rely on generic content, skip feedback, or introduce unfamiliar material may reinforce mistakes or disrupt the instructional sequence. Silent digital reading is not a substitute for oral fluency practice, particularly for early or struggling readers.

The fluency phase centers not only on efficient word reading but also on automatic access to meaning and coherence across text. As students move from effortful decoding to fluent reading, their cognitive resources are freed to support higher-level comprehension processes such as inference, integration, and reflection. In this way, fluency supports the transition from learning to read to reading to learn and is strongly correlated with reading comprehension (Fuchs et al., 2001).

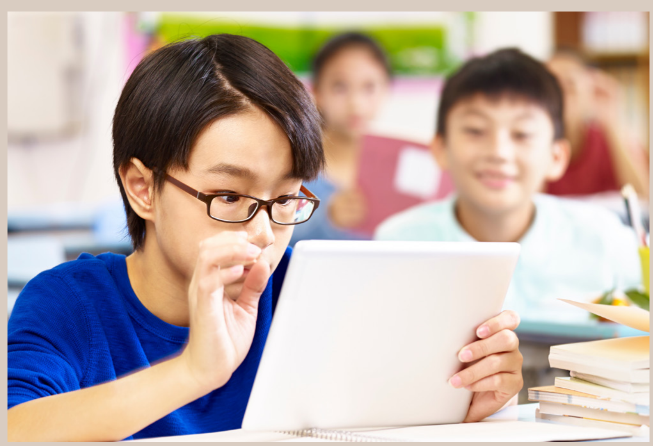
AI tools that support fluency must do more than track decoding accuracy or rate. They should reinforce meaning-making routines such as recognizing morphological patterns, interpreting sentence structures, and drawing inferences across connected ideas. Tools that prompt students to monitor for meaning, ask clarifying questions, or summarize what they have read can help develop semantic fluency as well as lexical efficiency. Work on meaning should be done thoughtfully so that comprehension monitoring does not interrupt the flow of text and students can confirm that they were accessing meaning as they read.

TEACHING **TIP**

Choose tools that build fluency across instructional levels and support word reading, as well as sentence- and passage-level comprehension. Fluency is as much about fluid understanding as it is about reading speed.

LEARNING **VIGNETTE**

A fourth-grade student, having mastered decoding multisyllabic words, uses an AI reading coach that highlights target vocabulary in a text about animal migration. As the student reads aloud, the system monitors prosody and accuracy, offering immediate feedback similar to a peer-assisted learning exchange. After key sentences, the AI pauses to prompt reflection, asking, ***"What does this word tell us about the animal's journey?"*** or ***"Can you explain why the penguin changed direction?"*** By alternating between supported reading and comprehension discussion, the student experiences an interaction similar to PALS routines, where reading aloud and responding to meaning-focused prompts reinforce each other. Over time, the student's reading becomes smoother and more meaningfully engaged, with automatic access to both word forms and their implications within the text.



GENERALIZATION / ADAPTATION

Learning Goal: *Promote transfer and application.*

These later phases emphasize transferring knowledge to new situations and adjusting responses based on novel demands. Generalization involves applying skills across tasks or settings, while adaptation requires flexible reasoning and metacognitive control. AI tools that support writing, project-based learning, problem solving, or research can facilitate these processes when they encourage deep thinking and independent application.

Well-designed generative prompts can scaffold reasoning and broaden background knowledge. Adaptive systems can extend learning by generating new practice materials that reintroduce taught concepts in novel contexts, embedding them across domains or content areas, and prompting students to connect prior knowledge to new problems. For example, a system might draw on previously learned morphological patterns during a science reading activity, or ask a student to apply knowledge of narrative structure when writing a historical account. These approaches promote flexible transfer by helping students recognize the relevance of what they have learned beyond the original lesson context.

Still, overreliance on AI to generate responses may reduce students' effort, creativity, and self-reflection. When students outsource thinking to the tool, they may struggle to develop the persistence needed for genuine transfer. If the tool's output exceeds the student's fluency level, it can overwhelm rather than extend learning.

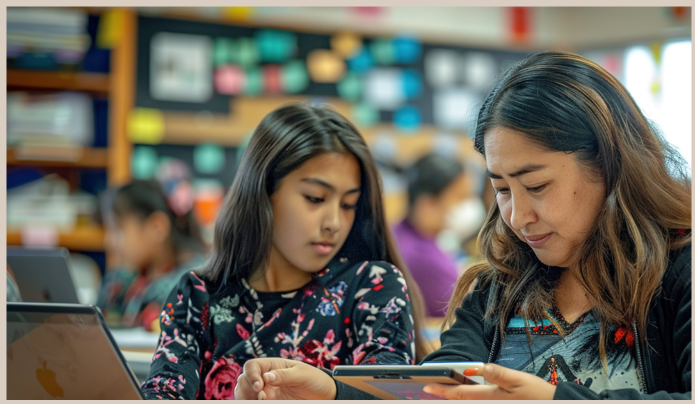
TEACHING **TIP**

Look for tools that prompt decision-making, support flexible strategy use, and promote independence. They should help students draw on both implicit pattern recognition and explicit reasoning.

LEARNING VIGNETTE

A fifth-grade student, having built fluency with key morpho-phonemic patterns (e.g., -***tion***, ***pre***-, ***graph***-), encounters a short science passage on ecosystems. The AI tool prompts the student to identify unfamiliar words, decode them using known morphological units, and then match them to meaning using sentence context. It highlights connections between the word ***"decomposition"*** in the text and previously taught words like ***"composition"*** and ***"deconstruct,"*** drawing on both explicit morphological knowledge and implicit pattern recognition. The student flexibly applies decoding, vocabulary, and comprehension strategies, showing evidence of generalization.

The teacher then facilitates a discussion comparing how students used different strategies to unlock meaning, reinforcing metacognitive awareness and strategic adaptation. This type of flexible application reflects both generalization (i.e., using known strategies in a new context) and adaptation (i.e., modifying those strategies based on novel demands).



Alignment and AI Integration

AI is not a replacement for structured, expert teaching. It is a tool that must be carefully aligned to the instructional phase, student needs, and curriculum. When used thoughtfully, AI can extend teacher capacity, reinforce critical skills, and support students at varying points in the learning process. However, without tight alignment to where students' skills are in the instructional hierarchy, AI tools risk delivering superficial engagement, misaligned practice, or unearned responses that shortcut authentic learning. Educators should select AI systems that are responsive to the demands of each phase, transparent in their instructional logic, and rooted in evidence-based practices. Tools that support accuracy in the acquisition phase, automate fluency-building practice, and scaffold deeper transfer and adaptation, while preserving cognitive effort, are most likely to support lasting literacy outcomes. Above all, AI should empower teachers and students, not replace the vital work of thinking, learning, and growing together.

GUIDELINES FOR RESPONSIBLE AI USE

AI tools hold promise, but only when their design and use align with how students learn. To ensure effective and ethical integration of AI into Structured Literacy instruction, we recommend the following principles.

1. **Align AI to Phase-Specific Learning Goals**
   AI tools should serve the instructional purpose of each phase, not flatten the learning process. Tools used for acquisition should support explicit teaching, accurate modeling, and practice. Tools for fluency must prioritize high-frequency, feedback-rich practice. Tools for generalization and adaptation should promote flexible thinking and deep transfer, not shortcut the work of learning.

2. **Preserve Cognitive Demand and Student Effort**
   AI should scaffold student effort and not replace it. This is especially critical for supporting implicit learning and fluency development, which depend on feedback-rich, high-dose practice. Tools that supply answers rather than hints may undercut long-term retention and transfer. At all phases, but especially in generalization and adaptation, tools must encourage active reasoning and metacognitive engagement rather than passive consumption.

3. **Ensure Instructional Alignment and Interpretability**
   AI tools must align with classroom scope and sequences, reinforce what has been explicitly taught, and avoid introducing unsupported practices (for example, learning styles or three-cueing). Systems should allow teachers to upload classroom materials such as curriculum maps or prior learning data to ensure alignment. They should also be transparent about how feedback is generated and when prompts are triggered.

   Well-designed systems can further integrate insights from cognitive science to respond to inter- and intra-individual differences in student performance. Fatigue, attention, motivation, and perceptual variability can all affect learning on a given day. Adaptive algorithms that adjust pacing, task difficulty, or modality in response to these factors can help sustain engagement while maintaining instructional integrity.

4. **Preserve Teacher Agency and Expertise**
   AI should support teacher judgment. Especially at advanced stages of learning, educators must retain control over how and when tools are used. High-quality tools allow teachers to customize supports, monitor progress, and adapt instruction based on real student data.

5. **Center Equal Access**
   Students who struggle with reading are often the least well-served by generic tools. AI must be researched across diverse populations and designed to meet the needs of vulnerable learners. Voice recognition systems, for example, must accurately process diverse dialects and accents. Misrecognition can erode confidence and hinder progress.

6. **Develop Field-Tested, Phase-Aligned Guidelines**
   The field needs clear, developmentally informed standards for AI integration across the instructional hierarchy. These guidelines should be developed through research–practice partnerships and include examples of effective use at each learning phase. Without such standards, tools risk reinforcing inequities or disrupting instruction. This includes protecting student data, ensuring transparency in how tools function, and maintaining human oversight of all instructional decisions.

ARE YOU ALIGNED?

SIX QUESTIONS FOR SELECTING INSTRUCTIONALLY SOUND AI TOOLS

To be dynamic, AI tools must be digital, but also could be leveraged to create physical copies of targeted learning activities if needed (e.g. developing practice passages and instructional content based on individual performance on last week's spelling test). Use these guiding questions to evaluate whether an AI tool aligns with how students learn and supports high-quality Structured Literacy instruction. Consider these six essential questions:

1. **Does it align with where students are in the learning process?**
   Instruction must match the phase (i.e., acquisition, fluency, or generalization/ adaptation).

2. **Is the tool reinforcing what has already been taught?**
   Premature or misaligned content can confuse or disrupt.

3. **Does feedback promote effortful learning?**
   Look for tools that foster spoken and written retrieval, not passive recognition.

4. **Can teachers monitor and adjust the tool's content and system use?**
   Transparency and educator control are essential. Educators will need to know how to leverage the tool's data in meaningful ways.

5. **Has it been tested with diverse learners?**
   Equal access and inclusion should be design principles, not afterthoughts.

6. **Does it amplify instructional depth or distract with novelty?**
   Tools should reinforce core teaching, not replace it.

RISKS OF AI USE
WHEN TOOLS UNDERMINE LEARNING

AI can support Structured Literacy instruction, but if poorly designed or misaligned, it can disrupt learning and deepen inequities. These risks are most acute when tools fail to reflect how learning unfolds across phases of instruction and memory systems. Moreover, AI integration must also account for student data privacy and governance, ensuring that personal information is protected and tools comply with ethical and legal standards. This includes protecting student data, ensuring transparency in how tools function, and maintaining human oversight of all instructional decisions. Data governance and privacy risks must also be proactively addressed as generative tools expand. This is especially critical when third-party systems store, model, or reuse student inputs or learning profiles.

1. **Undermining Cognitive Effort and Productive Struggle**
   Structured Literacy depends on effortful learning, retrieval practice, and timely feedback. AI tools that offer immediate answers or reduce challenges may short-circuit critical learning processes. When students are not required to actively retrieve, rehearse, or apply knowledge, they may appear fluent while failing to consolidate skills.

2. **Overloading Processing Capacity**
   AI systems that present too much content, use overly complex language, or introduce untaught concepts can overwhelm students' processing abilities. This is especially problematic during the acquisition phase, when attention, encoding, and integration must be carefully scaffolded. Poorly timed feedback, rapid pacing, or dense interfaces may interfere with focus and block learning from stabilizing.

3. **Flattening the Instructional Process**
   Some AI tools apply the same interface or task structure across all learning phases, failing to distinguish between early knowledge acquisition and later fluency or generalization. This can result in surface-level engagement rather than targeted, phase-appropriate learning. Tools must be sensitive to where a student is in the learning process, not just what content is being delivered.

4. **Instructional Drift**
   Even well-intended AI systems can slowly nudge instruction away from high-quality practices. For example, tools that favor engagement metrics may prioritize novelty over structure or introduce loosely related activities that dilute learning goals. Over time, this can erode fidelity to Structured Literacy and create confusion about instructional intent.

5. **Speech Recognition Errors**
   AI tools that rely on speech input, such as oral reading assessments or pronunciation feedback, may misinterpret students who speak with diverse dialects or accents. These inaccuracies can lead to false errors, erode confidence, and reinforce harmful assumptions about linguistic variation. Robust usability requires that AI systems be validated across different populations. While ongoing advances in speech recognition continue to improve accuracy, particularly for accented and dialectal speech, this remains an active area of development rather than a solved problem at this time.

6. **Misaligned or Inaccurate Feedback**
   Some AI tools provide automated feedback that is mistimed, vague, or incorrect. For students with reading difficulties, imprecise feedback can entrench misconceptions or generate frustration. Effective Structured Literacy instruction depends on specific, corrective feedback tightly aligned with instructional content and student performance.

7. **Eroding Transfer and Metacognition**
   AI tools that complete tasks for students, such as generating answers, sentences, or summaries, may reduce opportunities for active reasoning and self-monitoring. Over time, this can weaken students' ability to reflect on their learning, apply skills flexibly, and persist through challenges (Bjork & Bjork, 2011; Wolf, 2018). This ability is critical in the generalization phase. Transfer requires sustained mental effort, and AI should be used to support that process rather than replace it.

8. **Displacing Instructional Expertise**
   AI is not a teacher. AI is a tool that can enhance learning through additional practice opportunities. Relying on AI in place of professional educators, especially as a cost-saving measure, risks fragmenting instruction and weakening the quality of teaching. Structured Literacy depends on responsive, expert instruction that must remain central to student learning.

IMPLICATIONS for Implementation and Policy

As AI tools become more common in K–12 education, it is critical that their development, selection, and use reflect an understanding of how students learn and how instruction works. The following implications are offered for schools, educators, researchers, and developers seeking to integrate AI into Structured Literacy responsibly, effectively, and equitably.

What should schools and districts ask?

How does this tool align with the instructional scope and sequence?

- *Can the system be adapted to reflect the curriculum and students' developmental levels?*
- *What feedback mechanisms are embedded, and how are they triggered?*
- *How does the tool balance accuracy, feedback, engagement, convenience, and automation?*
- *Is the AI system transparent, explainable, and designed to preserve teacher control?*

What should educators look for?

- *Tools that provide phase-aligned support, such as providing explicit instruction for acquisition, guided practice for fluency, and opportunities for flexible application in generalization and adaptation.*
- *Features that reinforce what has been explicitly taught, rather than introducing unsupported or premature content.*
- *Real-time feedback systems that support reading accuracy, comprehension, and writing fluency.*
- *Student interfaces that maintain high cognitive demand and do not encourage passive use or over-reliance.*

What should researchers and developers prioritize?

- *Collaboration with educators to co-design tools that fit real classroom contexts.*
- *Field testing that examines how AI impacts retention, transfer, and independent thinking, not just short-term or superficial performance.*
- *Design frameworks that integrate principles from the science of reading, the science of learning, and structured literacy.*
- *Guardrails that reduce confabulations (e.g., false, misleading, or made up outputs), protect instructional fidelity, and avoid reinforcing non-research based practices.*

AI must be evaluated not only by how well it supports student learning, but by how well it teaches.

FINAL THOUGHTS AND CONSIDERATIONS

The rise of generative AI presents both opportunity and responsibility. These tools can amplify effective teaching, personalize learning, and expand access to practice and feedback. However, without careful design and thoughtful use, they risk reinforcing inequities for vulnerable learners, such as those with dyslexia, flattening instruction, and undermining student learning.

Innovation must be balanced with evidence. Tools that are exciting or appear promising are not always instructionally sound. Efficiency alone is not enough. Tools that save time or streamline tasks may still lack the instructional depth needed for real learning. Structured Literacy is grounded in decades of high-quality research. AI integration should likewise be grounded in high-quality research that demonstrates how best to leverage it and establishes its efficacy.

Moreover, instructional depth matters more than digital convenience. The goal is not faster answers or more content. Deeper understanding, durable skill development, and transferable knowledge support reading, writing, and thinking. Vulnerable learners must remain at the center. Students with reading and writing difficulties often benefit the least from one-size-fits-all tools. They need systems that respect developmental principles, learning processes, and instructional alignment. They need systems that provide more repetitions, practice, and opportunities to respond.

Educators, researchers, developers, and policymakers each play a vital role in shaping how AI is used in literacy instruction. AI can expand access to practice and feedback, and support consolidation of learning when its design and use are aligned with the science of reading, the science of learning, and the instructional sequence. Tools that support each phase of the learning process—whether they focus on accurate acquisition, fluent application, or flexible generalization and adaptation—are most likely to deepen learning and support skilled reading and writing. Well-designed tools should deepen teacher expertise and expand the number of students who experience lasting success. Student welfare and trust depend on it.

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Until everyone can read