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A Research-Based Proposal for Implementing an AI-Powered Digital Learning Tool for Writing Support in Higher Education

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Author's Note

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Abstract

The proposed research-based request of proposal (RFP) is an AI-driven digital learning tool, meant to assist in the support of writing-intensive course of first-year undergraduate writing courses in universities and colleges from the perspective of an Adjunct Professor teaching online courses at the undergraduate level including AI and Digital Literacy and English Composition. The suggested purchase is a dynamic tutoring and formative feedback system that is integrated intelligence with the institution's learning management system and will help to draft, revise, practice tasks, and monitor the work of instructors. According to the proposal, a well-managed AI tool will help solve the ongoing problems in higher education, such as slow feedback, unequal support to students, and insufficient opportunities to practice in a non-trivial manner, and it will also lead to resolve emerging non-trivial issues of privacy, bias, transparency, and academic integrity. The paper is based on the recent peer-reviewed evidence synthesizing evidence about the educational affordances of artificial and the circumstances under which the AI feedback can be perceived as helpful and the necessity of the human oversight in the assessment-rich environment. It subsequently converts that evidence into procurement specifications in the areas of pedagogical, technical, ethical, implementation, and evaluation. It provides three decision tools, including a table of feature-to-objective alignment, a weighted vendor evaluation table, and a table of phased implementation and budget. Overall, the proposal has shown that the most justifiable procurement plan is not to buy a generic AI application, but to buy a narrow scoped, available, secure, and instructor-controlled learning tool with stated educational goals and quantifiable implementation outputs.

Keywords: AI and digital literacy, AI in education, writing with AI, AI-enabled tutoring

Introduction

Artificial intelligence has ceased to be a peripheral innovation to become a core concern in the procurement of education. Over the past several years, universities have been experimenting with AI-enabled tutoring, automated feedback, adaptive practice, and analytics to relieve scale, responsiveness, and student support pressures. Recent surveys highlight AI in education as a wide domain that currently also involves personalized tutoring, intelligent assessment, profiling of the student and newer generative applications (Wang et al., 2024). Simultaneously, universities and colleges are being pressured by policy makers and accreditation bodies to enhance quality and timeliness of formative feedback, particularly in gateway courses were high enrolments limit staff ability. The educational argument of AI is thus very strong, but the procurement argument has to be far more disciplined than the technology hype cycle implies. The acquisition of an AI system in an institution must be made under circumstances where the educational issue is clearly defined; the conditions of implementation are sensible, and the conditions of governance are evident.

In this paper, a Request of Proposal (RFP) is proposed for an AI-powered digital writing aid to help first-year undergraduate students in writing classes at a hypothetical university. The suggested type of tool is an adaptive writing tutor and formative feedback platform that could be built into the learning management system and customized by the faculty and tracked by instructional designers and academic leaders. The reason why it is necessary to pay attention to writing is both practical and pedagogical (Henderson et al., 2025). Courses that feature writing tend to reveal chronic inequalities in preparing students, and the latter generally require repeated instructions as opposed to a single comment. Studies indicate that students value AI for its capacity to provide immediate feedback and support revision; however, they continue to compare it to teacher's feedback in terms of trust and precision (Malik et al., 2023). That is to say, as far as procurement is concerned, the tool should not substitute teacher judgment, but enhance it.

Problem Statement and Need for the Tool

The main issue which this proposal will solve is the fact that students require -frequent, low-stakes, formative feedback, but the institutions are not in a position to deliver such feedback continuously at scale. First-year writing intensive students need practice on how to plan, structure, paraphrase, cite, and revise several times. Faculty time is minimal, the classes may be very large and the traditional feedback loop may be sluggish (Liang et al., 2025). The writing and feedback tools (AI-assisted) can address this difficulty by offering feedback and guidance in real-time in the form of iteration as the drafting and revision stages proceed. In recent scholarship on AI in curriculum, instruction, and assessment, it is already observed that researchers in higher education have identified both benefits and challenges, including, faster feedback, support for teaching and learning, and potential reductions in routine workload, alongside concerns about output variability, misinformation and risk to academic integrity (Kasneci et al., 2023). This suggests that while AI has the potential to enhance efficiency and support instructional practices, its integration in educational contexts must be approached critically, with attention to issues of reliability, ethics, and pedagogical value.

Efficiency should not, however, be the sole way of framing needs. The value of education lies in the fact that the tool has to enhance the ability of the learner to interpret and respond to feedback. The conceptualized approach to this issue Liu and Deris (2025) put forward is that students should become AI feedback literate, i.e., learn to interpret, assess, and utilize AI-generated comments as opposed to absorbing them. Similarly, Venter (2025) demonstrates that the AI generated feedback can be fruitful in tertiary writing situations when it is strategically planned and combined with pedagogical architecture. The results justify the procurement strategy whereby learning design, feedback uptake, and instructor control are central in the RFP.

Literature-Grounded Rationale

The suggested type of tool is justifiable due to the fact that the existing literature leads to the balanced yet practical conclusion. On the one hand, AI systems will be able to assist in personalized learning, adaptive practice, and automated feedback in a variety of educational environments (Wang et al., 2024). ChatGPT and similar applications were also reviewed, and it was found that educators and students can use them to create explanations, examples, prompts, summaries, and writing support, which could facilitate more people to have immediate access to academic help (Crompton and Burke, 2024; Islam and Islam, 2024). Conversely, it is explicit in the literature that not just access to a generative model creates educational value. The issues that a procurement choice should respond to include hallucinations, bias, explainability, data privacy, and the risk of transferring core academic judgments to non-transparent systems (Crompton & Burke, 2024; Lim et al., 2025).

The best explanation of the evidence is neither uncritical acceptance nor wholesale rejection. Recent research on AI-enabled tutoring and student retention indicates that highly scoped AI systems may enhance access to academic assistance and mitigate friction in high-capacity or resource-limited environments, especially when the application case is limited and the system is a part of a more comprehensive support structure (Fierro Saltos et al., 2025). Also, studies on AI-assisted writing indicate that students like instant feedback and the ability to revise the text repeatedly, but they are still sensitive to the quality, authority, and trust (Henderson et al., 2025; Malik et al., 2023). As a result, the RFP ought to ask about a tool that is pedagogically constrained and outspoken of its constraints and clearly aimed at maintaining faculty in the loop.

Table 1 Alignment of Educational Objectives and Required Tool Capabilities

Educational objective	Institutional pain point	Required AI capability	Success indicator
Improve feedback timeliness	Slow marking cycles in large classes (Crompton & Burke, 2024)	Immediate draft-level formative comments and revision suggestions (Crompton & Burke,	Median feedback turnaround reduced to under 24 hours (Crompton & Burke, 2024)

Educational objective	Institutional pain point	Required AI capability	Success indicator
		2024; Henderson et al., 2025)	
Support student writing development	Uneven preparedness in academic writing (Kasneci et al., 2023)	Adaptive practice, exemplars, citation prompts, and scaffolded tutoring (Fierro Saltos et al., 2025; Kasneci et al., 2023)	Improved rubric performance in targeted writing criteria (Fierro Saltos et al., 2025)
Increase feedback uptake	Students ignore or misunderstand comments (Henderson et al., 2025)	Actionable feedback summaries, revision checklists, and comparison views (Henderson et al., 2025)	Higher student self-reported feedback use and revision completion (Henderson et al., 2025)
Preserve instructional oversight	Risk of over-automation and mistrust (Alfiras et al., 2025)	Instructor dashboards, approval settings, and editable prompts (Alfiras et al., 2025; Kasneci et al., 2023)	Faculty adoption with documented governance compliance (Alfiras et al., 2025)

Scope of Work

The RFP scope of work is minimal in scope. The university is not in need of a general-purpose chatbot to be used by students freely. Rather, it is searching a safe AI-based learning instrument geared towards formative writing assistance in the first-year courses. The vendor of choice will be supposed to provide software licensing, implementation planning, LMS integration, administrative configuration, faculty training and first year services (Wang et al., 2024). The fundamental teaching applications will involve thesis building help, draft revision help, source integration cues, citation verification cues and expert advice on clarity, argumentation, and structure. The tool should enable the instructors to set feedback limits, see how the students used it and turn off/limit the functions that can compromise course policy.

The educational dimension of this scope indicates one of the lessons of recent reviews AI tools are most effective when their educational goal is particular and when their application relates to the delivery of specific learning outcomes instead of generalized statements of change (Younas et al., 2025). An application that specifically assists in writing is also simpler to test compared to a product that suggests universalization of the personalization. The vendor then must show how the product aids formative learning, but not just content generation and how the administrators of the institutions can govern prompt libraries, model updates, data retention and reporting.

Requirements

The RFP must differentiate between technical, functional, pedagogical and governance requirements. The technical specifications involve LMS integration, single sign-on, role-based permissions, audit logs, cloud security documentation, interoperability standards, uptime, and compliance of the vendor to the relevant privacy legislation. Some of the functional requirements involve drafting, iterative feedback, revision history, instructor dashboard, usage analytics, multilingual customer support, access control, and administrator controls. Pedagogical conditions are congruency with the writing outcomes, facilitation of the formative assessment, clarification of feedback logic, and characteristics of the design that promotes revision but not answer replacement. The governance requirements encompass the clear disclosure of model restrictions, human oversight alternatives, incident reporting, and data minimization as well as the option to disable features that do not align with the institutional policy.

These are requirements that are based on the literature. According to Crompton and Burke (2024), generative AI tools can be used to help students learn, although they can also generate issues related to misuse and over-use. Alfiras et al. (2025) say that the governance issues prevailing in the use of AI in education relate to privacy, fairness, transparency, well-being, and accountability. Lim et al. (2025) also includes the perception of support, fairness, and instructional presence in the set of ethical evaluations students make towards AI-enabled assessment environments. As a result, educational RFP must not make ethics an appendix. The mandatory requirements should be laced with ethics.

Table 2 Mandatory and Preferred Requirements for Vendor Responses

Requirement domain	Mandatory requirements	Preferred requirements
Technical	LMS integration, SSO, audit logs, encryption in transit and at rest, FERPA/GDPR-aligned controls	Learning tools interoperability certification and API-based analytics export
Functional	Draft upload, revision suggestions, dashboard analytics, role-based controls, support ticketing	Rubric-linked feedback templates and multilingual interface options

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Requirement domain	Mandatory requirements	Preferred requirements
Pedagogical	Faculty-configurable feedback settings, revision-oriented prompts, citation support, no autonomous grading	Discipline-specific writing modules and embedded exemplars
Accessibility and inclusion	WCAG 2.1 AA conformance statement, keyboard navigation, screen-reader compatibility	Personalization supports for multilingual and neurodiverse learners
Governance	Bias monitoring statement, data-retention settings, transparency documentation, human review pathway	Third-party bias audit or institutional co-governance model

Evaluation Criteria

Evaluation of the vendor must indicate the educational intent of the purchase, rather than just the functionality of software. Pricing is an issue, however, not to overrule the choice to take a product that does not satisfy the pedagogical, governance and implementation needs. The studies of AI-assisted feedback indicate that students assess AI feedback as useful and trustworthy as teacher feedback, which means that the quality of products and design integrity is the focus of their adoption (Henderson et al., 2025). Owing to this reason, the evaluation matrix must place heavy weight on pedagogical alignment, governance readiness and user experience, as well as integration and value-for-money.

The process suggested is a two-stage review. Initially, the proposals are verified by the procurement staff and instructional technology specialists according to the required standards. Second, shortlisted suppliers receive a scoring on a weighted rubric and are asked to do a live demonstration on instructional scenarios established by the university. Such demonstration must involve a faculty perspective, student perspective, dashboard perspective, and description of how the model addresses the issue of uncertainty, policy controls and inaccurate output. Institutions that use the tool in writing-intensive environments should also be required to conduct reference checks.

Table 3 Recommended Vendor Evaluation Matrix

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Criterion	Weight	Rationale
Pedagogical alignment and feedback design	25%	Must support revision, learning outcomes, and instructor-controlled formative use
Privacy, ethics, and governance	20%	Must provide transparency, data protection, human oversight, and policy controls
Usability and accessibility	15%	Must be intuitive for students and staff and demonstrably accessible
Technical integration and scalability	15%	Must integrate with LMS/SSO and perform reliably at institutional scale
Implementation support and training	10%	Must provide onboarding, documentation, and change-management assistance
Evidence of effectiveness and references	10%	Must show credible higher education use and measurable outcomes
Cost and total value	5%	Cost matters, but should not override educational fitness

Implementation Timeline and Budget

The implementation plan must be done overtime to minimize the institutional risk. Two or three first-year writing-intensive subjects would be much better than full-campus deployment. It has been recommended to take six months between award and the first pilot cycle to be evaluated. The first month shall involve contracting, data privacy review, technical planning, and course choice. The second and third months will include integration, prompt configuration, faculty training and accessibility testing. The pilot should start in the fourth month, and the trends of use and escalation of the issues should be observed closely. Months five and six should entail assessment, faculty debriefing, gathering of student feedback and a scale or stop decision.

The budget must reflect as a total cost of ownership instead of a line of licenses. Besides licensing, the institution must estimate the setup, training, change management, integration support, and evaluation. Theoretical pilot-year cap in a mid-sized public university can be between $90,000 and

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$150,000 based on volume of students, maturity of product, and the complexity of integration. Such an investment is only rationalizable in the event that the tool provides statistically significant enhancement to the access to feedback, student revision behavior, and faculty workload in specific situations. The RFP must compel vendors to distinguish between one-time and recurrent costs, and clarify any use-based cost assumptions.

Table 4 Illustrative Implementation Timeline and Budget

Phase	Indicative timing	Key deliverables	Illustrative cost (USD)
Procurement and contracting	Month 1	Final scope, legal review, security review, vendor selection	$10,000–$15,000
Integration and configuration	Months 2–3	LMS integration, SSO, prompt setup, admin controls, testing	$25,000–$40,000
Training and pilot launch	Month 4	Faculty workshops, support materials, go-live support	$15,000–$25,000
Pilot operation and evaluation	Months 5–6	Usage analytics, surveys, learning evidence, decision report	$40,000–$70,000

Proposal Submission Instructions and Terms

The revised version of RFP should instruct the vendors to submit a narrative proposal, an implementation plan, security and privacy documentation, an accessibility statement, a schedule of prices, a reference list, and a sample service-level agreement. Not less than four weeks of the release with optional question period and addendum process are required before the proposals are received. Late submissions should not be received except in a case where there is an extension issued to all the vendors. The university should be at liberty of rejecting any offers, seeking clarification and demonstrating the products prior to awarding.

The terms and conditions must involve anticipations of confidentiality, proprietorship of institutional data, secondary use of student data to train models, breach notification, audit rights, anticipation of up-time, reaction time to audit, and termination. Given the rapid evolution of AI systems, the contract also needs to mention that the vendors should disclose the major changes in the models, alterations in the data processing patterns, and updates that alter the functional scope of the product. It aligns with the current literature on governance where transparency and human accountability are brought out as the primary requirements of responsible adoption (Alfiras et al., 2025).

Conclusion

An effective RFP of an AI-powered digital learning tool should have a clear educational issue, and not an abstract interest in innovation. The literature also justifies the acquisition of narrowly focused AI tools that enhance access to feedback, scaffold revision, and aid learning in high-enrollment contexts, but also cautions that educational AI creates risks related to privacy, unfairness, over-dependency, and loss of pedagogical authority (Crompton and Burke, 2024; Lim et al., 2025). The proposal prepared in this case is in response to that evidence, and it established guidelines for a platform of adaptive writing tutor and formative feedback, specifically for first-year courses in institutions of higher education. Its reasoning is explicitly conservative: purchase a tool when the institution is capable of defining the learning outcomes, implementing the governance controls, and assessing the pilot with explicit standards. In that case, an AI-driven learning tool can serve as a viable educational support tool instead of a hypothetical technology purchase.

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The Intersection of Reading and Instructional Technology in Education

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Abstract

Since the invention of instructional technology, there has been a strong correlation between literacy skills and technology. Technological tools have been used to enhance the teaching and learning process for students of all ages and abilities from Pre K to the collegiate levels. As technology continues to evolve, learners continue to use these tools to meet their literacy needs and enhance their overall learning and success in their respective educational settings. This literature review will explain how technological tools and resources have been used to enhance reading and literature skills using elements of universal design principles and professional development all while being mindful of the types of learners and their varying needs.

Keywords: assessment, K-12, literacy, higher education, instructional technologies, remediation, reading

Introduction

Reading instruction is the bedrock of teaching and learning in K-12 educational settings. It is also a critical component in the teaching and learning process in higher education across the content areas. When children learn to read, it opens up channels for them to start the process of reading to learn about a variety of topics. Reading instruction in schools started from the inception of schools in the United States dating back to the one room schoolhouses. Early reading instruction was provided using a variety of texts and resources such as the New England Primer, the American Primer and Readers, and the McGuffey Readers that was published by William Holmes McGuffy in the 1900s. However, before most of the early readers, there was the Bible which served as both instructional and religious material for the settlers of the colonies. The content of these early reading materials provided guidance for living successfully in the community (*History of the Book*, n.d.).

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However, as society grew and changed, so did the type and delivery of reading instruction. Additionally, focus shifted from only being able to read at the foundational levels to being literate citizens. With literacy being a skill that was needed for upward mobility and progress, the federal government helped in shaping the trajectory of American education. Federal and state laws advocated for accountability and equitable practices for all learners and enforced that children of a certain age be enrolled in school (Katz & Phi Delta Kappa, 1976). Therefore, to comply with these mandates, measures were put in place to ensure all students were reading effectively and demonstrating grade level proficiencies. Learners who struggled with meeting grade level proficiency were often supported with additional resources. However, with the invention of the computer and other technologies, educators began to use them as aids in teaching, remediating, and enriching learning. These technologies and tools helped to ensure students were meeting standards and demonstrating grade level proficiency. As a result, computer assistive instructions (CAI) became a part of the teaching and learning process. While computer assisted technology is now a staple in the teaching and learning of reading instruction in educational settings, this was not always the case. It was not until the 1980s that this mode of instruction was introduced (James, 2014). Since its introduction into the classroom, CAI has proved to be a force multiplier in promoting reading and literacy skills across the curriculum at all levels of learning (i.e., K-12 schools, higher education settings, vocational and technical education, and other learning spaces). Educators at all levels use computer-based technologies (CBTs) and tools to diagnose and remediate reading difficulties. They also used technologies and tools to enrich student learning and provide additional support for students with learning differences and those whose first language is not English. Instructional technology has become a conduit that helps learners achieve academic success including those with special needs (Rice & Dunn, 2023).

Although the technologies and tools that were originally used to support reading and literacy development, and learning in other content areas could be considered rudimentary, and sometimes sparse, now, there are thousands of tools, resources, and technologies that are student friendly and easy to use. These modern technologies serve a variety of purposes in education and range from enhancing student learning, remediate learning difficulties, to serving as a tutor or interactive partner in education. This article will highlight a few of the tools and technologies used at the elementary and secondary levels of instruction. It will also examine how tools are used in higher education and other adult learning settings to enhance reading and literacy skills. The article will also provide insights into how tools and technologies are used to increase English language learner's and students with learning differences literacy skills at all levels of instructions. To a lesser degree, the authors will examine the impact of professional development on teachers' knowledge and ease of use of the technologies. They will explore the teacher's ability to effectively use the tools to enhance student's reading and literacy skills using technologies that are available to them.

Exploring the intersection between reading instruction and technology usage is important at all levels of education. This is necessary because technology and instructional tools and resources aid in preparing American citizens to be ready to compete in the global marketplace. According to the NCES (2024), American children's performance showed a decrease in scores on the most recent National Assessment of Educational Progress (NAEP) assessment in reading comprehension which is given every two years. The report indicated that students in grades four, eight, and twelve performed less well than the years when the test was administered (National Center for Education Statistics, n.d.). Therefore, it is necessary to examine how reading is being taught and what are some of the technologies used at the various levels to support and promote literacy skills acquisition and comprehension. Having this knowledge will help in determining measure to promote better reading scores and increase reading and literacy skills for American learners at all levels of the education continuum.

Reading and technology in the elementary grades

Using Technology to Diagnose Reading Ability and Proficiency

Reading and literacy instruction has been one of the foundational skills taught in the beginning stages of the learning process (History of the book, n.d.). The teaching of literacy skills sometimes start as early as a child begins to show signs of cognition. In other settings such as day care and pre-school, early literary skills are being explicitly taught to prepare children to become literate individuals who will succeed in the later grades. In the formalized school system, professionals often begin literary based instruction in pre-schools, voluntary pre-kindergarten, and kindergarten programs, and continue this formalized instruction through the elementary grades. Literacy and reading related instruction are also taught in various other educational settings, and across other content areas using a variety of tools, resources, and technologies based on learner needs, availability and types of technology. As knowledge increases and technology becomes a part of every aspect of life, it is now used to support the teaching of various literacy-based instruction. In recent years, technology-based reading instruction and assessment practices have been found to be effective and reliable in interactive, holistic approaches to literacy within a structured and blended learning model. Through the strategic use of multimodal learning formats, deliberate selection and integration of high-quality digital tools for increased fluency and comprehension, connection to contextual media for real-world communal literacy skills application, and delivery of data-driven insights informing critical targeted reading strategies, technological tools have helped to enhance literacy instruction exponentially.

In a recent meta-analysis of current technology-based interventions for elementary students with reading difficulties, Alqahtani (2024) analyzed the overall impacts of such interventions on long-term reading acquisition and achievement across grades K through 5. His findings suggest that technology-based reading interventions are “an effective approach for improving the reading skills of elementary-aged students with reading difficulties” (Alqahtani, 2024, p. 7). Additionally, educators can also utilize the integrated diagnostic assessments and adaptive learning paths within digital literacy platforms to structurally target reading difficulties for wider student groups of varying ages, grade levels, and developmental stages as consistent supplements to traditional intervention methods that heavily incorporate hands-on explorations of printed media.

When considering any and all positive influences of modern technology on administering accurate and accessible diagnostic measures for reading ability and proficiency, it becomes necessary to lean towards a critique of common classroom-based practices which aim to consistently use selected digital tools as a means of complementing general reading instruction, enhancing students' active exploration of authentic reading tasks, and proactively accommodating diverse learning needs. It is especially noteworthy to find emerging studies that speak to the effective and efficient reading platforms most commonly used with general education students and those experiencing ongoing reading- and language-based difficulties. Results should then indicate significant gains when supplementing classroom reading instruction with the implementation of an educational/reading technology program. This could bolster reading outcomes for students with reading difficulties as well as reinforce universal reading depth and contextual application for all students. Additionally, Hurwitz and Vanacore (2022) emphasize that for such digital literacy platforms to enable maximal reading achievements and mitigate foundational reading skill difficulties, it is necessary to identify specific intervention-based technologies addressing "multiple skill areas" (p. 463) and routinely implement the "full suite of program resources over a sufficiently extended period" (p. 463) to foster blended, multi-sensory engagement of deep reading practices in both print and digital learning spheres.

Relating to these fundamental aspects of responsive teaching and adaptive learning modes, one of the most sudden yet inevitable shifts in traditional education emerged because of the complex challenges and limitations brought by the COVID-19 pandemic (Angwaomaodoko, 2024). The long-term closing of educational institutions and suspension of face-to-face learning processes led to a more widespread reliance on intentional online instruction and digital diagnostic tools (Angwaomaodoko, 2024, p. 87), that were intended to effectively replicate relevant and meaningful classroom techniques in remote settings while expanding access and enhancing personalization through adaptive, self-paced learning technologies.

Reading instruction and assessment practices are by no means isolated from these continuing developments in a post-pandemic era. Research has demonstrated how diagnostic literacy platforms such as Lexia and I-Ready have significantly accelerated students' positive development of reading comprehension and fluency skills by using adaptive practice and personalized intervention strategies with strict fidelity in classrooms (Hurwitz & Vanacore, 2022; Pane et al., 2023; Randel et al., 2020, and Schechter et al., 2015). The structured implementation of these literacy platforms provides digitized supplemental activities to traditional curricula (Randel et al., 2020). They utilize students' benchmark diagnostic results to target multimedia instruction in alignment with gradual progress monitoring, real-time lesson difficulty adjustments and scaffolds across key domains. These instructional technologies provide consistent data reporting that highlights precise skill strengths and identifying notable areas of difficulty in reading (Hurwitz & Vanacore, 2022; Schechter et al., 2015).

While the main (and perhaps most obvious) benefit of using adaptive, data-driven literacy platforms in conjunction with traditional reading instruction practices is the increased ability for both targeted and interactive student practice with foundational reading skills such as phonological awareness, word recognition, structural analysis, and automaticity/fluency, of higher cruciality may very well be the implications of these platforms for students who have had repeated experiences with reading difficulties and perceived failures in their comprehension and application (specifically, students with varying reading ability differences) (Alqahtani, 2024; Hurwitz & Vanacore, 2022; MacArthur et al., 2001). It is worth noting that the aforementioned rapid shift in technology integration across educational institutions—as a widespread "adjustment" to the

COVID-19 pandemic and subsequent distance learning protocols—has established, a new cultural landscape "in which digital skills are absolutely part of the repertoire needed for every child" (Richardson, 2014, p. 17). Moreover, truly effective literacy instruction in today's digital world naturally requires a flexible approach to assessing individual student reading abilities and proficiencies by "linking challenging text with multimedia sources" (McKenna, 2014, p. 11). Therefore, it is important to strike a balance between traditional reading skills and emerging yet increasingly common digital literacy supported tools, technologies, and practices. Having this balance is necessary because there are a plethora of tools and technologies that are used. Educators, parents, and a variety of stakeholders must sift through the various tools and technologies to determine which best suits their students' learning preferences and their unique needs—and sometimes budget. For example, some of the current technological based literacy tools used to support literacy learning in the elementary grades are ABC Mouse, Alpha Blocks, IXL Reading, Epic, Star Fall, I-Ready, Khan Academy, and Lexia to name a few. There are also a variety of other literacy sources such as online libraries and virtual textbooks. These can be accessed from a variety of devices such as iPads, tablets, smartphones, laptops, and desktop computers. While some of these are free, some require a paid subscription. However, most schools purchase site licenses and students can access these programs through their schools for free.

The following is cursory review of Lexia and I-Ready as two highly effective research-based literacy platforms utilizing adaptive technology for authentic diagnostic assessments of reading ability and proficiency. They aim to provide insights relating to the necessity of integrating developing technology-based learning tools into every student's "reading repertoire" (Richardson, 2014, p. 17). They serve as holistically supportive measure for structured remediation and targeted intervention addressing both ongoing reading achievements and difficulties.

Lexia Core5 Reading

As a premier example of utilizing technology to enhance reading comprehension and fluency, Lexia is an interactive literacy platform providing a suite of science-based reading solutions which aim to integrate and actively engage multiple areas of literacy and language. It uses both digital and teacher-led activities that incorporate multisensory learning materials (e.g., graphic organizers, flashcards, decodable readers, fluency passages, etc.), higher-order collaborative thinking extensions, oral language supports, and contextual skill application assignments (Hurwitz & Vanacore, 2022). The platform's combination of print and digital learning opportunities serves to uphold the blended learning approach by allowing students an independent, self-controlled exploration of and practice with targeted reading content (still within a structured, sequential needs-based order), while supporting face-to-face learning processes that addresses foundational literacy skill strands.

In particular, the platform's supplemental *Core5 Reading* program for grades PK-5 offers the rationale that technology-enhanced reading solutions whose scope and sequence is directly informed by and aligned to the expanded Simple View of Reading has the maximized capacity to create critical learning pathways tailored to students' specific needs and goals relating to decoding and language comprehension skills development (Hurwitz & Vanacore, 2022). The design characteristics of Lexia Core5 for sustaining reading achievement and improving reading difficulties focus on providing systematic and explicit "multi-component instruction" (p. 454) to build a comprehensive, interconnected understanding of six foundational literacy strands across authentic real-world contexts.

In a study exploring the efficacy of a blended learning approach to reading instruction targeting English Language Learners (ELLs) and those from lower socio-economic backgrounds, it was found that students in grades 1 and 2, showed the most progress with the use of the Lexia Core5 program (Schechter et al., 2015). This program targeted appropriate reading skill levels through extensive practice and adaptive scaffolding (i.e., initially assessing student performance in the online program, then curating paper-and-pencil reinforcement lessons for highlighted areas of difficulty) that were directly related to the level of fidelity in which teachers actively used Lexia Lessons and Skill Builders in their classrooms. Additionally, intentional high usage paired with teacher-led explicit instruction and scaffolding measures consistently informed by Core5 diagnostic results can effectively accelerate the learning of "even the lowest-performing students" (Pane et al., 2023, p. 8) and lead to substantial reading achievement and gains across grade levels.

For the online components of the Core5 program to successfully build and deliver actionable intervention resources targeting problem areas in reading, teachers had to "provide in-person support when program data made it clear that students were struggling to master specific skills" (Hurwitz & Vanacore, 2020, p. 9). Those data pointed to the essentiality of ongoing diagnostic results in the program-based curation of highly structured lessons targeting major skill gaps (Schechter et al., 2015). Leveraging real-time data from students' Core5 placement experiences to supplement traditional reading instruction ultimately means striving to "meet the individualized usage targets the software sets for each student" (Pane et al., 2023, p. 8). It provides every student with tailored multimodal lessons which follow a gradual release format to "help target teacher-led instruction and monitor progress" (Schechter et al., 2015, p. 196).
In their 2020 study, Hurwitz & Vanacore found that students were two times more likely to achieve increased proficiency in reading because of the stable implementation and usage of Lexia's Core5 Reading program as a comprehensive literacy intervention over the course of a single school year. Notable gains in reading proficiency were observed that resulted from consistent student interactions with the computer-based components of Core5 (anywhere between 20 to 80 minutes per week. The gains were also attributed to simultaneously involved intentional, routine teacher modeling and use of targeted reading skills both in the platform and daily classroom instruction (Hurwitz & Vanacore, 2020; Pane et al., 2023).

I-Ready

Curriculum Associates (2020) describes I-Ready as a research-based, adaptive reading support program assisting students in grades K-12 in their reading and math instruction. It provides personalized lessons that "give explicit instruction and extensive practice, offer supportive feedback, and build conceptual understanding" (p. 3). This program assesses and support student learning whether students are at, below, or above grade level. This includes English Language Learners (ELLs), and students with reading disabilities. The digital program administers a tailored instruction plan with a "differentiated starting point" (p. 3) based on student performance levels using its I-Ready Diagnostic. This diagnostic aims to precisely target students' grade-level abilities

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and skills in connection with Common Core standards, adjusting difficulty to provide scaffolding for struggling readers and advance student mastery through more intensive, engaging learning challenges.

The subsequent online lessons produced by the I-Ready Diagnostic place students on a "personalized, scaffolded" learning path (Randel et al., 2020, p. 9). It targets specific skill deficits and key areas of mastery, integrating evidence-based multimedia instruction (e.g., appropriately leveled literacy and source texts/high-interest e-books, skill-building games, engaging graphics/visual resources, language supports, complementary paper-based learning materials, etc.) and adaptive online assessment measures that provide student-centered literacy skills practice and contextual application opportunities paired with "rigorous standards-based classroom instruction" (Forsman, 2018, p. 27). Performance data in I-Ready "allows teachers to add lessons and/or adjust the lesson sequence provided to an individual student or group of students" (Curriculum Associates, 2020, p. 3). It focuses on both digital and traditional instruction on comprehensive foundational literacy skills coverage across key domains. These domains include phonological awareness, phonics, high-frequency words, vocabulary, and comprehension of literary/informational texts.

In particular, the I-Ready learning platform incorporates "intentionally designed" *Stretch Growth* targets directly informed by students' starting performance on the Diagnostic (Rome & Daisher, 2022, p. 1). This information helps to create a structured learning path toward grade-level reading proficiency. As outlined in Forsman's (2018) dissertation, a study was conducted to determine if the I-Ready program was effective in meeting the collective reading and math development needs of students. It was also conducted to makes a compelling case for the I-Ready Diagnostic as a "highly predictive benchmark for the results of each student's state testing scores" (p. 26). Relating to this precise design characteristic, I-Ready Stretch Growth targets serve to move students both with average reading growth and repeated difficulties beyond typical grade-level gains toward a more accelerated yet attainable "one- or multi-year path toward proficiency" (Rome & Daisher, 2022, p. 1). A study conducted by Gates (2024) aimed to understand elementary teachers' perceptions of their consistent use of I-Ready in classroom settings and the platform's overall impact on designated RTI students' reading achievement. Gates notes that "to hear teacher voices and perspectives on an RTI intervention tool is essential to providing students with the best learning experience and growth results" (p. 4). Specifically, the perceived benefits of I-Ready on student reading achievement appear to be focused on structured, data-driven differentiation, ongoing progress monitoring, supplemental resources for explicit classroom modeling and practice, and tailored accelerated paths for successful achievement of milestones (through the function of I-Ready's Stretch Growth targets).

Moreover, a high degree of implementation fidelity for the I-Ready program is just as essential in maintaining best practices across print and digital learning spheres. Student data collected within the platform must be frequently and carefully analyzed and reviewed to effectively integrate supplemental instructional materials and to accommodate literacy skills reinforcement strategies. This should be conducted over a consistent period of time, as well as to create and sustain a literacy-based learning environment grounded in authentic exploratory processes targeting specified skill deficits and areas of mastery in reading. The extent to which educators are fully

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supported and made capable in enhancing their classroom instruction using a technology-based literacy platform like I-Ready will ultimately determine the maximal effectiveness of diagnostic results and the associated data-driven program suggestions for multi-modal interventions.

It is worth noting that the potential positive effects of technology on the literacy development and achievement outcomes of students with reading difficulties will entirely depend on the integrity of its design, the established learning purposes and goals it is intended for, the quality of accompanying classroom-based instruction that concretely conceptualizes targeted literacy skills, and student characteristics influencing successful print and digital reading acquisition (e.g., prior knowledge, learning preferences, cognitive differences, socioeconomic backgrounds, etc.) (MacArthur et al., 2001, p. 298). Both Lexia and I-Ready have proven to be efficient and effective reading technology platforms that combine computer-based learning with teacher-led reading activities designed to utilize a diagnostic approach to create personalized, data-driven learning plans for all students. Such technology-based literacy platforms guide students in overcoming reading difficulties and improving reading comprehension beyond the levels of growth that would normally occur without the use of technology. Yet evolving over a considerable amount of time, there is evidence indicating that technology-based interventions may prove to be essential supplements to traditional instruction and intervention practices for students of varied reading ability. The correct application of literacy platforms like Lexia and I-Ready frames these adaptive, personalized education support as effective tools that must individualize reading instruction as well as provide appropriate interventions for students at varying ability levels. Educators must strive to naturally integrate targeted technology-based literacy lessons and/or supplemental materials into their traditional instruction practices "as part of the implementation model" with strict fidelity to ensure the programs deliver positive reading results for all students (Schechter et al., 2015, p. 195).

While reading instruction paired with technologies and tools to support reading and literacy instruction continues to be a part of the education process, it is important that efforts are made to strengthen educator's professional development. This is necessary because when educators are effectively trained in the processes of using these technologies and tools, they will be better positioned to use the technologies to automate the teaching and learning process, provide additional enrichment opportunities for learners whose results on the various diagnostic assessments indicates that the student is proficient and or above grade level, and to use these resources to support reading and literacy skills across other subject areas. Effective training on these two platforms will also aid teachers in using remediation features to attain grade-level proficiency.

Reading and Technology in a Special Education Context

Learners with special needs have had to overcome more challenges in educational formalized settings and as a result there have been several laws put in place to ensure they receive a free appropriate public education (FAPE) in public educational settings (*Individuals with Disabilities Education Act (IDEA)*, n.d.; *ECTA Center: Federal Laws and Regulations for AT*, n.d.). Similar measures are in place in private schools, colleges, universities and various other types of educational institutions. One strategy that is used to support the needs of students who fall under

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the special education umbrella is to provide them with a variety of information communication technologies (ICTs), and others assistance based technological tools and devices to support their learning needs. These technologies range from aiding with mobility in the classrooms to using various audio and visual related technologies to help in the acquisition of reading, writing, and other communication and literacy related skills.

The use of instructional technology is crucial in special education. To provide students with quality instruction and support their access to an appropriate education, teachers must be familiar with the tools that will best serve each of their unique students' needs. In recent years, studies have found that a diverse group of students with disabilities have expressed interest in Artificial Intelligence (AI) technologies to determine how this "new" technologies could better serve their learning needs. Some of the students who have expressed interest have varying disabilities to include those who are diagnosed with autism spectrum disorder, intellectual disabilities, language and learning disabilities, dyslexia, visual impairments, and multiple disabilities (Olakanmi et al., 2020; Rice & Dunn, 2023; Starks & Reich, 2022). Assistive technological (AT) devices and services are primarily used for students with an Individualized Education Plan (IEP), as they facilitate easier access to the learning process. Accessible Education Technology (Accessible Ed Tech), on the other hand, offers universally designed options that may be useful for all learners (Sbatista, 2025). Even though students with moderate-to-severe disabilities are often excluded from literacy activities by teachers and parents, studies have shown that young learners with intellectual disabilities who use Augmentative and Alternative Communication (AAC) devices can acquire phonological awareness and decoding skills when instruction is adapted. With carefully scaffolded materials and measurements such as baseline data collection, posttest, and follow-up, some students have shown gains in phonological skills and decoding (Ulriksen et al., 2024). Research on shared-reading stories found that students who read daily score higher on measures of vocabulary, comprehension, and decoding. It is also important to note that the most effective read-alouds are interactive (Galea et al., 2025). There is also evidence indicating there are benefits in repeated reading of stories. While it may not always be possible to have a teacher or parent re-read stories multiple times, there are various technologies that can support repetition for learners. As a result of the repetition, read- alouds, and various other interactions with literature and technology, special needs children's questions and comments often increase and become more interpretive. Expressive communication skills improve as well when books are discussed, children discover the joy of books, and comprehension of spoken language is enhanced. As a result, the learner constructs meaning through interactions with the reader—which in some cases may be interactive or augmented technology. Lastly, the student's knowledge of the world is broadened, and their cognitive skills increase.

Some school districts purchase eBooks and databases specifically for use as reading resources. To comply with federal and state mandates and to support learners with varying abilities, they also provide accessible instructional materials to eligible K-12 students with an IEP and a documented Print Disability. Such tools provide access to curriculum, improve independence, and enhance the learning experience by converting printed and digital text into accessible formats— thereby positively impacting student performance. Another reading resource offered by some school districts is Learning Ally (2025). Although it is not primarily designed for students with learning differences; with this tool, students can access audiobooks, including literature selections, by

purchasing an individual membership through the Learning Ally app, available for computers, smartphones, or tablets. Using audiobooks can prove to be an accommodation strategy for learners of all ages with various learning differences as it may help to relieve them from the cognitive load associated with reading if they have various learning challenges such as ADHD which impacts focusing for extended periods of time.
Bookshare, Chrome Reader Mode, and Immersive Reader are also reading tools that assist students with learning difficulties. Bookshare provides students with print disabilities with the ability to use accessible books (DiGiovanni, 2020). Chrome Reader Mode removes clutter, ads, and distractions while allowing users to customize text and viewing preferences. Immersive Reader is a free tool from Microsoft that utilizes proven techniques to enhance reading skills. The program reads text aloud, separating words, breaking down syllables, and identifying parts of speech. It also translates, provides definitions, explains pictures, and visually simplifies the page.

K-12 teachers in public school settings view this as a great resource for their students and asserts that inclusive and assistive technological tools are essential for all students, particularly those with special needs to thrive. Assistive technologies are designed to create accessible classrooms and support daily life skills for students with special education needs (Hoogerwerf et al., 2021; Zilz & Pang, 2019). They consist of a range of devices and services that work to support students in augmenting existing abilities, compensating for, or bypassing difficulties students may experience (Chambers, 2020).

Assistive technologies also support all learners through Universal Design for Learning (UDL). UDL is a set of principles for curriculum development that provides all individuals with equal opportunities to learn (Almeqdad et al., 2023). In a K–12 elementary context, UDL offers multiple representations, hands-on, and scaffolded opportunities that help students with language disorders or learning disabilities engage and access content in reading and it facilitates writing skills acquisition. Studies conducted on children with ADHD have shown that UDL-based interventions are more effective than traditional personalized teaching strategies in fostering basic learning skills (Frolli et al., 2023).

In addition, there are school-based resources that facilitate learning through strategies that foster success and diversity in the classroom for all learners. Several keyboarding resources, such as ABCYA, Dance Mat Typing, Doorway Online - Single Handed Typing, Doorway Text Type, Talking Typer Online, Typing Club, and Typing Master Online Typing Test, are quick, easy, and practical tools that assist and guide students in the classroom. They provide accessibility and practice for the student to enhance their reading and writing skills. The integration of these keyboarding resources in the school setting constitutes an effective strategy for advancing inclusive and equitable literacy acquisition practices. The tools mentioned exemplify the pedagogical potential of digital technologies to enhance students' literacy development through accessible and engaging learning experiences.

Additionally, in several educational environments across the United States, one technology that is used for a variety of purposes is Google Workspace for Education. It can be used from upper elementary grades onwards. However, it differs from the Google consumer account because it complies with federal student privacy laws, does not display advertisings, and offers unlimited

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storage (Gracias, 2025; Shimalla, 2024).Some of its features include a variety of collaborative productivity tools that are available anytime, as well as the ability to sync bookmarks and passwords across devices, supporting best practices for teaching and learning. Other tools used in educational settings for reading and writing activities and to support students with learning differences are the visual collaboration tools called Lucid Chart and LucidSpark. LucidChart is a collaborative diagramming product that enables teachers and students to create flowcharts, graphic organizers, mind maps, and other non-linear information displays. They allow students to engage in the learning process by brainstorming or demonstrating their work using a different mode of presentation. LucidSpark, on the other hand, is a virtual whiteboard that connects teachers and students, allowing them to bring their best ideas to life (The World's First Work Acceleration Platform, 2025). A final technological tool to highlight that continues to support literacy initiatives is the Project-Based Learning Checklist Creator. It is a tool that allows students to choose from a list of guidelines for class projects, creating a checklist for each project type, including writing, presentation, multimedia, or science projects. While this tool may seem commonplace and mundane for the neurotypical learner, it is a game changer for neurodivergent learners. The benefits of such implementation include increased students' reading and writing competencies, digital fluency, and differentiated learning. The more teachers invest in their self-efficacy and positive attitudes toward digital technologies to address the diverse needs of contemporary classrooms, the more likely they are to use them (Carvalhais et al., 2025).

Technologies and tools used in middle and secondary schools

Although it is expected that students in middle and high schools should have mastered reading and literacy skills needed to be successful at this level, the reality is that a vast majority of secondary aged learners are still considered struggling readers. According to the 2019 U.S. Department of Education Nation's Report Card, 27% of all eight grade students were scoring below the basic reading levels. In the same report, the percentage of students with disabilities who scored below the basic reading levels more than doubled for that same grade in comparison to that of the general population. The report noted that 63% of students with disabilities were failing in basic literacy skills (National Center for Education Statistics, n.d.). Similar statistical data shows that students in grades 6-12 are struggling with reading and literacy skills including those who are considered neurotypical learners. As a result, reading and literacy skills are still being taught at the secondary level. These skills are integrated into some content area courses and in some cases, there are specific reading courses for students who need help remediating reading difficulties. In the secondary schools, Reading, Writing, and English are often combined and coded as ELA courses. However, being that secondary grades students are closer to adulthood and should be ready for college and career, there are other forms of media and digital literary skills that are being taught in conjunction with regular literacy skills.

Although reading and literacy instruction may look different in the middle and secondary classroom, there are some similarities with the content that is being taught in elementary schools. Students are still being taught fluency, vocabulary, and comprehension skills based on individual needs. In some cases, students are even being taught phonics-based instruction based on diagnostic results from I-Ready or whatever diagnostic instruments the secondary school uses. However, being that students are at the stage where they are reading to learn, a greater emphasis is placed on reading comprehension (Stevens et al., 2022). Students are asked to read a variety of materials and make meaning of what they read. As a result, the technological reading and literature-based resources that are afforded to the adolescent and teenage learners are focused on providing information on, and exposure to a variety of topics. For example, some of the online resources and applications that are provided to these learners are Gale in Context, Follet Destiny, Varsity Tutors, and a host of others based on school and district's choice. These resources provide students with access to articles, images to critique, achieved collection items, access to college and career resources and so much more. While these resources may not be readily available at the student's fingertips, classroom teachers, media specialists, guidance counselors, advisors, and mentors within the education systems often direct students to these technologies and tools that will enhance their reading, technology, and literacy skills. Some of these applications and resources also help students to develop their digital literacy skills either through direct instruction or self-paced, self-directed tutorials. When focusing on comprehension skills, the student must demonstrate an understanding of what was read by answering questions using either multiple choice or extended response formats (Capin et al., 2022). However, in recent years, more emphasis has been placed on secondary students providing responses using written responses. The premise is that when students can demonstrate comprehension of text using the writing process, it helps them to think more critically about content and look at varying perspectives (Stevens et al., 2022). When students are asked to write their responses, they are often forced to "read" the text and support their responses with textual evidence. Additionally, when students provide written responses, it helps teachers to better assess students' levels of reasoning.

Being that many textbooks are now digital, when students use their online textbooks, they may access and respond to questions online using various technologies and tools such as their tablets, iPads, laptops, or other mobile devices. To illustrate, when some grades 6-12 students use their Harcourt Mifflin Harcourt Ed platform (HMH) to access their ELA course material, they can engage in a variety of reading and literature activities. For example, students can engage with their instructors through chat and messaging features, complete both in class and homework assignments, use the adaptive learning features for tutoring and additional support or they can use the embedded feedback sections to learn from the adaptive textbook and improve on their work. There is also AI features embedded in the Writable component of the platform that allows students to edit and correct their written response for a variety of writing related errors (*Writable | 3-12 Writing Practice & Assessment | HMH*, 2025). Being that this is an interactive learning platform, it also allows students to engage in both formative and summative assessments all in one place.

In addition to the textbook features and the Writable component of the HMH platform, there are other components such as Read 180 that support basic reading and literacy skills such as phonics and fluency and progress all the way up to comprehension. As previously noted, students at the secondary school level should have mastered basic reading skills, however, for those who have not yet mastered basic reading skills, technology is helping them to learn the skills. Another way that technology supports students in the areas of reading and literature is using audio-visual technology. Secondary school libraries have purchased thousands of literary materials and have made them available as audio books for students who are still learning to read, those with cognitive deficits who needs to see and hear text read to them, learners whose first language is not English, and other reasons too numerous to mention. Some of the materials are also made available in assorted sizes and types of texts, fonts, and sizes to facilitate learning differences.

In secondary schools, several technological tools and applications are also used to assess, remediate, and enhance reading skills. As a result of most programs being adaptive and interactive, it meets students where they are and helps them move to the next stages of their literacy development based on the amount of time and effort they put in. Some of the programs used by the secondary school students are also the same ones used to assess and remediate reading difficulties at the elementary level. For example, I-Ready and IXL are programs that are designed to perform the same functions for students in grades K-12. However, IXL is very diversified and provides tutoring and support in a vast array of subjects. To illustrate, students in secondary schools can use IXL's test prep features to help them prepare for college placement exams such as SATs and ACTs. Those who are more career focused could use these features to prepare for the military's ASVAB test or GED exams. It can also provide support for learners in Science, Social Studies, Biology, Spanish, and several other subjects. However, although IXL is so diverse in its offerings, there is a section of this application that is wholly dedicated to reading. It can be used by both parents and educators for progress monitoring, remediation, and as a teaching assistant or tutor. The adaptive learning platform provides feedback and tutorials to students when they get a question incorrect.

As the national report card and other reputable data gathering sources indicate, American students are falling behind in Reading. Therefore, as middle and high school educators and administrators work to increase Reading skills, it is important that they take a closer look at the tools and technologies that they use to support their students' learning needs. While several of the tools are designed to increase Reading skills, if educators are not familiar with the back-end usage, the students may not get the best results irrespective of the tool or technology (Capin et al. 2022). Teachers should be trained in a variety of reading tools and technologies to aid in maximizing student growth and success. Educators should be able to effectively gather, read, and analyze students' data produced by these technologies to make informed decisions. Being able to perform these functions will allow all educators to move students along if they are showing growth, pull them for individualized instruction if the data demonstrates a need, or refer them for other supports and services that may better suit their learning needs.

While the technologies highlighted in the above sections are inclusive of reading skills acquisition and information literacy skills in the K-12 classroom, there are variations in the way these tools are used based on a variety of factors. Some of the factors include the cost of the technologies and tools, learner preferences and abilities, educator's proficiency levels, and the time and infrastructure available to support the technologies. There are similar reasons that explain the type and usage of technologies to support reading and information literacy initiatives in higher education and other adult education learning spheres.

Reading and Technology in Higher Education

Students who enter higher education spaces are expected to possess the reading and literacy skills needed to successfully navigate this space whether they enroll in online classes or in brick-andmortar face-to-face classes (Bawa, 2016; Murniati et al., 2023). However, this is not always the case as students are enrolling in higher education from a variety of educational, language, cultural, age groups, socio-economic, and language backgrounds. Some of these various backgrounds have not effectively prepared students with the knowledge and skills needed to successfully handle the rigors and requirements of American higher education institutions. Therefore, some higher education institutions, especially community colleges, have made provisions to provide a bridge for students who need support in reading and literacy skills, computer and technical skills, and basic self-directed skills (*Encouraging Students to Read |Center for Innovative Teaching and Learning | Northern Illinois University*, n.d.). Providing these skills is necessary to promote retention efforts because students who do not have the support and resources needed may attrit out of their programs more readily.

To reduce high attrition rates and promote student success efforts, some institutions have provided direct reading instruction classes for students who need this type of support. On the other hand, other institutions have provided reading instruction in conjunction with other foundational and technical support in their various first year success courses or other first year success initiatives directed to retain students (Dunn, 2024). In these courses, students learn a variety of reading strategies to enhance their vocabulary, comprehension, and reading speed. Higher education institutions that provide direct reading instruction also use a variety of technological and computer aided assessment tools and programs to diagnose student's level of reading abilities. Most of these assessments are administered and scored using computer-based software. For example, students may take the Accuplacer Reading diagnostic which is a computer adapted assessment that is created by The College Board to determine student's level of reading proficiency for placement in college classes. Scores from the assessment may show that a student is proficient in reading and can go directly to college level English classes or it may show that the student will need more academic support in the areas of reading comprehension and vocabulary (*Home - ACCUPLACER | College Board*, n.d.). Other computer-based reading assessments that are administered to college students to determine placement are the McGraw Hill Connect Reading Diagnostic, and the Reading Plus diagnostic to name a few. Diagnostic reading results allow higher education personnel to place students in classes that will help them gain the skills needed to be successful in their academic pursuits. While the above listed computer assisted diagnostic tests are used to diagnose reading levels, abilities, and placement levels, the creators of these assessments also provide users with opportunities for remediation and enrichment. Some institutions use the programs as teaching tools and have partnered with the companies as textbook providers or resources to help students in a plethora of ways.

In addition to the above resources, there are also other computer-based reading and literacy programs that are used to increase reading rates and fluency. For example, the Ace Reader program is one that is used in a variety of settings. It is an award-winning software program that is designed to increase reading speed, comprehension, and fluency. Students can use its various features to practice increasing their focus to become faster readers. This tool has been used in higher education, industry, and even the military to promote overall learner success and it has a track record of over 20 years of use in education (*AceReader - Reading Speed, Comprehension and Fluency Software*, n.d.). Some other tools that are used to enhance comprehension and critical thinking skills include digital annotation, audiovisual resources, interactive games, online

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discussions, and digital storytelling (Tar, n.d.). Digital annotation refers to the practice of adding notes, comments, questions, or multimedia elements to a text through an online platform or software. This strategy empowers students to engage more readily with texts and fosters interactive learning experiences. Platforms such as Kami, Hypothesis, and Perusall enable learners to collaborate actively by identifying literary elements, establishing connections, and sharing insights with peers. Through this process, students not only develop individual comprehension but also build a sense of community as they collectively contribute to the annotation process. Thus, the use of digital annotation tools helps to foster a dynamic and collaborative approach to textual analysis in educational settings.

In addition to teaching reading and literacy skills that adult students need to be successful across higher education spaces, institutions also provide other forms of literacy skills such as information literacy. Being that adult learners in higher education are expected to be self-directed and independent, the premise is that they should know how to navigate the landscape and be able to access and use the available institutional resources. However, when students lack the skills needed to access and use the available resources, this often poses a problem. Therefore, similarly, to providing reading, language, and other literacy related support, some institutions provide students with support in information literacy. Providing reading and technical skills in the form of information literacy either directly or indirectly is one of the strategies that is used to promote retention efforts and student success. In one study, it was also reported that students indicate that technical skills are one of the skills they need to be successful in colleges and universities (Dunn, 2024).

It is necessary for students to have information literacy skills at the college level because having these skills enables students to independently locate and use resources such as the library. While information literacy is a broad term, it encompasses various forms of technology-based literacy skills to include digital literacy, media literacy, computer literacy, and networking literacy. These are all skills needed to be successful in higher education (Deepmala et al., 2021).
Some of the needed skills that are taught to students under the information literacy umbrella are how to effectively communicate with a variety of stakeholders using Information Communications Technologies (ICTs) such as emails, communicating through the institution's learning management system, or other platforms such as Microsoft Teams or Zoom platforms. Other skills that are also taught under the information literacy umbrella are how to effectively use the library for research, and how to network.

While not all students who enter higher education need assistance with literacy and or technology related skills to succeed, research shows that these skills help all students when completing a variety of learning related tasks more effectively and efficiently (Wang et al., 2022; Bergman, 2024). For example, students who are tasked with reading a vast amount of information may use a variety of reading strategies or technological tools to help them manage their time and to complete their assigned reading with fidelity. With the invention of audio recorded books ―which have now branched into textbooks, students can now listen to their textbooks and learn the content while performing another less cognitively demanding task. Having most textbooks and course materials online, students now have a variety of ways to use technologies and tools to support their learning. In addition to listening to their textbooks, if the student is a visual or kinesthetic learner, they can also interact with their reading materials on the computer using the features that are available to them like bookmarking, highlighting, and annotation just to name a few. If they are asked to respond to questions in their online textbooks or course materials, students can respond anywhere and at any time once they have access to the Internet. Student have the ability and capability to perform a variety of tasks such as editing their work if the auto corrected feature is turned on to help them see errors in their responses, they can communicate with the professor from their textbook, and they can even use the help feature to assist them with vocabulary and comprehension. Professors may also support student learning and comprehension by making course materials more interactive and engaging by using technology such Wevideo. With Wevideo, professors can place questions at strategic check points to help learners process and interact with the materials. Other interactive tools that can be used to support learners' comprehension of course materials and promote engagement and interaction is Voice Thread. This is a technological tool that can be integrated into any content area to promote deeper learning and engagement while promoting critical thinking, and enhance the humanizing aspect of teaching and learning, while also developing effective speaking and listening skills (*Highered*, n.d.). Voice Thread is a computer-based technology that has been revolutionizing teaching and learning in higher education in a variety of ways and has helped thousands of students achieve academic success in higher education.

As technology continues to evolve, there are always more advanced technologies and tools that are created to support reading and literacy initiatives in higher education. With the increased use of artificial intelligence in educational settings, AI tools are also used to support reading and literacy initiatives. One such tool that is gaining momentum in a variety of higher education teaching and learning spaces is Google Notebook LM. It is an AI-powered tool that can help students to sort through journal articles to determine if they are the best sources when the abstracts do not provide enough information. Notebook LM has the capability to transform written documents into podcasts and other audio which allows students to listen to their course materials while on the go (Metha et al., 2024). Being that Google Notebook can be fed up to twenty documents at a time, the information it provides is more content specific and tailored to the individual user's needs. Unlike chatbots that produces information from a more generalized data source, Notebook helps its users to automate and streamline work that is tailored to a specific need (Metha et al., 2024). Having this tailored information helps learners with comprehension as it may help them to explain areas, they find confusing or even generate questions to help them think through and clarify written material. It may also help writers who need help clearly expressing themselves. Notebook can help the user by analyzing their writing and making suggestions for improvements or it may also provide critiques to help the reader examine their own written work. Although Google Notebook is still in its infancy stage, it is shaping up to be a powerful tool for students and instructors alike. In fact, several universities that have site licenses have provided access to students to create their first Notebook accounts to use for a variety of purposes as they work to complete their program of study (*NotebookLM*, n.d.).

Professional Development for Curriculum Content in Reading and Technology

School districts and administrators must ensure that teacher training and support is front and center of their plan for effective classroom discourse. While schools are provided with the

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latest technologies and tools to support student learning, teachers' professional development should be paramount when considering these technologies. Simply providing teachers and students with devices or software is not enough. Although teacher professional learning has become an area of growing interest as teacher shortage continues to impact schools across the country, effective professional development that results in changes to improve teacher practices needs to become a priority. This is necessary because effective and meaningful professional development plays a critical role in helping students develop the complex skills and learning outcomes required for success in the 21st century. Professional development that integrates curriculum content and 21st-century technological skills with teaching strategies is crucial for supporting teacher learning in classroom contexts (Darling-Hammond et al., 2017).
Studies have shown that the integration of technology into professional development for teachers is necessary for the implementation of successful student use of technology in the classroom (Booth, 2012; Wang et al., 2022). When teachers understand how technology and content are connected, they learn how to integrate tech tools into their lessons, improving the adoption of these resources (Flewelling, 2024). However, strong tech integration in K-12 education does not necessarily correlate with being a "new" or younger teacher or educator, or an active social media user. Educational technology use, effectiveness, and overall support for skill development should be factored in the creation of teacher education and continuing education programs for all teachers. When educational technology usage and integration is perceived as a valuable component in the educational setting, professional development opportunities, and funding to support its use will not fall lower on the priorities list (Flewelling, 2024). When veteran teachers are trained in the use of the newer technologies that can be used to improve and enhance their students' reading and literacy skills, they will be more apt to use these tools. Consequently, with the increased use of educational technology to support learning, professional development focused on technology integration has become a significant area of attention during and after the COVID-19 pandemic. Such professional development opportunities have given teachers access to online resources, the ability to collaborate with peers, and tools and platforms for assessing and reflecting on their professional learning. The learning opportunities also enable educators to engage in more accessible, personalized, and impactful training (Huan et al., 2024). Additionally, monitoring the fidelity of use is crucial, and the assistive technology must be used regularly, in meaningful ways, and in alignment with instruction.

Regardless of the educational setting or the types of learners, instructional technologies and tools continue to serve as a force multiplier in the teaching and learning of reading and literacy skills. As the use of these tools and technologies increase, more emphasis is now being placed on professional development to put educators at the forefront of literacy adaptation and innovation.

Conclusion:

Reading skills are an integral part of education at all levels (i.e., K-12 settings or higher education). Reading and literacy skills are used to learn content in all subject areas and grades. Students first learn to read using a variety of reading strategies as they learn to identify letters, sound out words, blend letters, segment individual phoneme sounds, learn new vocabulary words, and eventually begin to draw meaning from written sources. Learning these basic reading skills has been enhanced and supported over the years with the use of various interactive and engaging technologies and tools in the K-5 educational settings. However, as students progress in grades and the focus shifts from the learning to read, to a reading to learn phase, they continue to use a variety of tools and technologies to support their knowledge acquisition. There are technologies and tools that support literacy acquisitions and development for all learners. This includes learners whose first language is not English as well as learners who may be experiencing learning challenges due to varying disabilities or limitations. To ensure that learners are provided with the best tools and technologies available to meet their education needs, professional development opportunities for educators should be an integral part of the conversations that promote literacy skills at all levels. As globalization, migration patterns, cultural and socio-economic factors continue to impact education across the US, cultural and intercultural competencies should be factored into professional developmental offerings as well as instructional offerings and course designs. Educators must recognize and value students' linguistic and cultural diversity, adapt their teaching methods, and promote inclusiveness. This involves not only acknowledging diversity but actively integrating inclusive practices to ensure that students' backgrounds are seen as vital to the learning process. By incorporating culture, technology, and diverse backgrounds into literacy and language instruction, teachers can empower students to become confident, competent, and literate learners who can use a variety and technological tools to support their learning needs in a globalized society (Chaves-Lovorn, 2025).

Regardless of the learning challenges that readers may face, technologies and tools are available to help in diagnosing, remediating, and enriching literacy skills at all levels. Literacy skills acquisitions and technology integration as a support for this endeavor have forged a symbiotic relationship over the years. With the new development and increased use of artificial intelligence in educational settings, this relationship will only continue to grow as educators learn new ways to use technologies such as Generative Artificial Intelligence—GenAI to support reading and literacy initiatives in all educational settings and subject areas.

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Teaching Adolescents to Read Purposefully with Generative AI

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Abstract

Existing treatments of generative AI in literacy instruction tend either to list competencies without theoretical grounding or to offer practice-focused reflections without a mechanism for generalizing across reading contexts. This synthesis takes a different approach for the adolescent grade levels that have received less attention than K–2 or postsecondary contexts. It uses the RESOLV model of purposeful reading (Britt et al., 2017; Rouet et al., 2017) to derive the specific challenges generative AI poses to readers' development of context models, task models, process decisions, and motivation—all important pieces of the deep comprehension that purposeful reading should yield. From that same architecture, the synthesis derives five instructional strategies that educators can teach students to use to support deep reading of complex texts while preserving their intellectual autonomy and advanced reading skills. The piece concludes with an argument for the importance of AI literacy that is specific to the demands of schooling.

Keywords*: adolescent literacy, AI literacy, deep reading, generative AI, large language models, reading comprehension, reading instruction*

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Introduction

This article contributes a theory-derived framework for learning from texts with generative artificial intelligence (AI), explaining why specific reading comprehension and learning challenges arise and deriving instructionally actionable strategies from that theory. The introduction of large language models (LLMs) into educational contexts brings with it many opportunities but also many challenges for the teaching and learning of adolescent literacy. There has been no shortage of think pieces about how teachers should use generative AI in their planning (Ferlazzo, 2025; Gecker, 2025) and teaching (Smigielski, 2025), how students are using it (Dumin, 2024) or should not use it (Grose, 2025) for reading and writing, and what it will mean for our individual and collective intelligence in the coming years (Kosmyna et al., 2025; Rothman, 2025). And this all comes despite the evident drawbacks of its development and adoption (e.g., resource-intensive computing, data-scraping without consent, uneven accessibility in various communities).

In all this discussion, primary and postsecondary education appear to have received the majority of scholarly and popular attention. For primary school teachers, chatbots for engaging with LLMs may offer unprecedentedly customizable support for differentiating reading (and other content) instruction in students' earliest years—for example, the U.S. Institute for Education Sciences' CELaRAI research and development center for teaching K–2 reading with the support of generative AI. For college and university instructors, the drawbacks of generative AI appear more salient than the benefits (American Association of Colleges and Universities & Elon University Imagining the Digital Future Center, 2026). LLMs' ability to produce convincing prose is pressing professors to make a new and stronger case for students to put effort into analytical thinking, reading, and writing tasks (Hudd et al., 2025)—especially as the workplaces graduates will enter are increasingly adopting generative AI tools (U.S. Census Bureau, 2026).

So what about adolescent students, those in secondary grades (middle school and high school in the US, Key Stages 3–5 in the UK), who are sandwiched between those primary and postsecondary levels? These students were in their formative years of primary school when their education was severely disrupted by the COVID-19 pandemic (Howard et al., 2021; U.S. Government Accountability Office, 2022). Now, they are continuing to make up ground, but more slowly than the field had hoped (Kuhfeld & Lewis, 2025; National Assessment Governing Board, 2025). And today's adolescents are faced with this new generative AI technology that could upend the demands that school and the working world will place on them as readers and writers. What will their literacy learning look like in these unprecedented circumstances?

That adolescents are already engaging with this technology at scale is not a hypothetical: recent survey data indicate that a large and growing majority of secondary-age students report using generative AI tools regularly for school-related tasks, including reading and writing assignments (Cardon et al., 2023; Dumin, 2024). Emerging empirical work raises urgent questions about the consequences. Studies of college-age students, the cohort immediately upstream of today's adolescents, find that AI-assisted writing is associated with reduced neural engagement in language and executive function networks compared to unaided writing, with heavier AI users showing the most pronounced decrements (Kosmyna et al., 2025). Research on critical reading has shown that adolescents are particularly susceptible to accepting fluently written text as credible, regardless of its actual accuracy or sourcing (Macedo-Rouet et al., 2019), a vulnerability that AI's confident, articulate output is well-positioned to exploit. Further, a growing body of survey-based research finds that secondary teachers feel underprepared to guide students' AI use, and that professional development addressing generative AI and literacy specifically remains scarce (Graham et al., 2025). The present synthesis responds to that convergence of need and evidence.

The purpose of this theoretically grounded synthesis therefore is to help teachers of adolescent students, and the scholars who study adolescent teaching and learning, understand and address the challenges and opportunities that generative AI affords for this age group, particularly in the domain of deep reading comprehension (Allen & McNamara, 2020; LaRusso et al., 2016; Pearson et al., 2020). Existing treatments of generative AI in literacy instruction tend to either list competencies without theoretical grounding or offer practice-focused reflections without a mechanism for generalizing across reading contexts. This synthesis takes a different tack. It takes as a starting point an existing account of (traditional) reading comprehension—the RESOLV model of purposeful reading (Britt et al., 2017; Rouet et al., 2017)—that emphasizes how purposes shape readers and reading activities and therefore lends itself to application to reading in the context of AI. We use that model to derive, rather than identify, the specific ways AI disrupts adolescent readers' context models, task models, process decisions, and motivation—and to derive corresponding instructional strategies from that same architecture.

To keep in close contact with practice, we first present an instructional unit typical of expectations of today's adolescent readers. Next, we adopt a specific, well-validated model of reading comprehension, the RESOLV framework (Britt et al., 2017; Rouet et al., 2017), as the theoretical architecture through which we identify and analyze the challenges generative AI poses for adolescent readers. From this framework and its emphasis on how reading tasks and contexts shape readers' process decisions, we derive the challenges and corresponding strategies that follow. We then present seven challenges posed by generative AI for adolescent literacy, discussing what it looks like for students to learn to overcome those challenges and use LLMs in responsible and effective ways. Each challenge is grounded in established theory and relevant empirical research on adolescent reading, cognition, and learning; and each of the five instructional strategies we present is similarly warranted by evidence from the reading and self-regulated learning literatures.

The article therefore complements recent pieces on AI literacy that has discussed domain-general competencies that are needed to engage effectively with AI, such as work by Casal-Otero and colleagues (2023) and Su and colleagues (2023), and with generative AI in particular, such as the proposals from Annapureddy and colleagues (2025) and Kasneci and colleagues (2023). Here instead, we apply our expertise as cognitive scientists and digital literacy scholars to focus on how this technology can and should be used for school-based reading (and writing) activities, in the vein of current proposals by Hutchison (2024) and Kalantzis and Cope (2025).

Establishing Common Ground: A Sample Reading Task

While myriad literacy-related activities can now be undertaken in collaboration with LLMs, in this article we seek to help educators support students' use of generative AI chatbots as they pursue deep reading comprehension. To ground the following discussion in an authentic example, we point the reader to a sample literacy exercise from the *Core Knowledge* science curriculum (https://coreknowledge.org), specifically from Unit 5 of its eighth-grade materials (roughly aligned with Key Stage 3; https://www.coreknowledge.org/free-resource/cksci-unit-5-genetics/). Early in that unit, students are expected to read a collection of texts on *Muscles and Other Traits*, a topic about which they have some but not extensive knowledge; comprehend those texts; and synthesize what they learn into a target literacy product (i.e., an infographic on building muscle). The texts differ in form (image-heavy vs. straightforwardly expository), type (podcast transcript, advertisement critique), and register (conversational vs. formal). In the discussion that follows, we explore how generative AI can support a student engaged in this specific *Muscles* reading activity, from planning to read to producing their final synthesizing assignment.

Engaging Generative AI in Purposeful Reading: Guidance from the RESOLV Model

Our approach to identifying and overcoming the challenges presented by generative AI (described below in *Challenges, Masterful Solutions, and How to Get There*) is inspired by the RESOLV model of reading comprehension (Britt et al., 2017; Rouet et al., 2017), which takes reading to be an activity aimed at solving a problem set out in a specific context (hence RESOLV: REading as problem SOLVing). According to RESOLV, purposeful reading has the following four crucial characteristics (also depicted in Figure 1):

1) **The specification of a context model**: When a student decides to read something, they inherently use a context model to structure their reading approach. This involves understanding the specific context in which the reading will take place and determining the conditions or purposes for reading. For example, in a classroom setting where a science teacher explains an assignment (like reading a text about muscles and creating an infographic), students apply their context model. This includes their understanding of classroom dynamics, instructions provided, typical expectations for their reading and writing, and what kind of support is considered acceptable. Often, these context models are held implicitly by students and teachers. However, they can become explicit through deliberate actions like setting norms and working on shared assumptions, ensuring everyone has a common understanding of how to approach reading and learning together.
2) **The adoption of a task model**: In a reading context, purposeful readers adopt goals reflecting their personal interpretation of what they are asked to do in a context. For an assignment like developing an infographic based on the *Muscles* texts, students might have different strategies: one student might focus on identifying and using relevant images from the texts to interpret the information; another student might start with an existing infographic template and fill it with their background knowledge before even reading the texts. These individual approaches influence how the texts are read and understood, leading to varying comprehension outcomes. For this reason, the task model tends to be updated dynamically throughout the reading process as readers find themselves getting closer to or farther from their reading goals.
3) **Wide-ranging process decisions that proceed in an interactive fashion (rather than a linear one):** Regardless of the identified context model or specific reading task and goals, there are usually many ways to satisfy goals. Readers typically do not make all decisions about how to approach a text up front. Instead, they adjust their strategies as they read.

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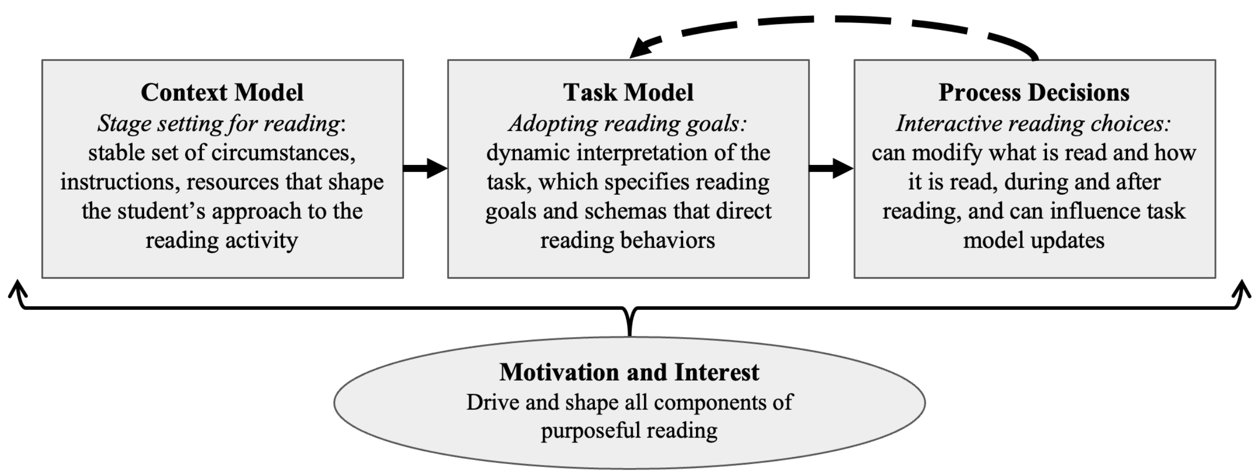
These decisions can involve a need to: seek external information, ascertain the relevance of current information, reread or reflect to deepen understanding, and determine whether a reader's goal has been satisfied (and if it has not, the reader may decide to choose a new action or indeed a new reading goal; Britt et al., 2017).

4) **Motivation and interest:** A reader's motivation to complete a reading task and their interest in both the task and the content can shape the way they engage in all three of the above components of reading.

All of these components have highly salient applicability to reading with generative AI. It is an educator's responsibility to set up circumstances in which students will arrive at an appropriate context model. This includes explicit expectations about (a) what reading is for, (b) how generative AI can and should be used, (c) what the goals of a specific learning activity and the class as a whole are, and more. With an adequate context model, students are then prepared to adopt a salutary task model and articulate goals for the reading activity that can help the reader decide what kinds of prompts and indeed even which LLM to use, as well as when to first consult an LLM relative to reading the focal text. Recognizing that these are distinct constraints—what the context affords, what the student takes the task to require of her, and what the student hopes to achieve with it—is important if we are to support students' understanding of what chatbots can do to further their reading comprehension. It is also important if we are to convey to them that reading comprehension is *their* achievement, not the chatbot's. As such, even when reading with the interactive support of LLMs, readers need to remain responsible for their own goals, their own iterative process decisions, and for sustaining their own motivation and interest to succeed at any reading task they take on.

Figure 1

Depiction of the Four Main Features of the RESOLV Model That Apply to Reading With Generative AI



With this grounding in a model of purposeful reading, we turn next to describing seven specific challenges that reading with generative AI poses to adolescent readers, and along with those challenges also present what masterful engagement looks like and how to help students develop that mastery.

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Challenges, Masterful Solutions, and How to Get There

The seven challenges that we have identified for students reading with generative AI may be encountered across a range of reading activities. For every challenge, though, there are lessons to be learned from masterful users of generative AI and from other expert readers—and there are ways to take those lessons and teach students to apply them in their own work. As we discuss each of the challenges, we also offer characterizations of how students can become skilled readers and users of generative AI in ways that are less likely to jeopardize their opportunities to learn.

Challenge 1: Prompt Dependence

The language a user uses to prompt a response from an LLM shapes its output in ways that are complex but also predictable (White et al., 2023); it is perhaps for this reason that the concept of "prompt engineering" has made its way into the public discourse more than any other specific skill related to engaging with generative AI (Eliot, 2025; Jacobs, 2025). Prompt engineering refers to the act of designing and structuring inputs to generative AI interfaces to guide their probabilistic text generation toward a user's desired outputs (Chen et al., 2025). Becoming a strong "engineer" of these prompts is key to getting chatbots to produce the output a user desires (Giray, 2023), while poor prompt skills can hinder interactions with LLM chatbots and lead to outputs that do not respond to the intentions of the user.

Within the RESOLV framework, prompt dependence is most directly an obstacle to the formation of a productive task model. When a student's prompt is imprecise or poorly formed, the chatbot's output may not correspond to the student's actual reading goal, undermining the iterative alignment between goals and strategies that purposeful reading requires. Research on self-regulated learning corroborates this concern, suggesting that learners who do not articulate clear task goals before seeking external support are less likely to benefit from that support and more likely to accept off-target information as sufficient (Zimmerman, 2002).

Masterful engagement addressing this challenge entails the generation and critical refinement of effective prompts. A prompt is effective if it elicits the intended output from the chatbot. A masterful user can enhance prompt effectiveness by:

- making explicit their own assumptions about a topic,
- specifying the format in which they expect a response,
- giving examples of what they expect the output to look like,
- asking the chatbot to give step-by-step reasons as it prepares its output (chain-of-thought prompting), and/or
- instructing the chatbot to expressly critique its own output.

To avoid challenges posed by the prompt-dependent nature of LLMs in reading comprehension, students should learn to set explicit goals for their tasks to guide chatbots effectively. Using templates like RAFT (role, audience, format, topic) can streamline prompt creation, helping students craft prompts that produce reading-supportive outputs. Additionally, students should

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recognize the extent of their agency and responsibility for eliciting their desired output in this process.

Challenge 2: Alignment of Text to Context

Depending on the reading activity, students may find the LLM's output either helpful or unhelpful. Variations in structure, tone, and content can challenge understanding, especially when students expect the AI-generated text to share characteristics with the focal text. To what extent a chatbot's output should (or should not) align with the text a student is working to comprehend is subject to the teacher's discretion and the curricular expectations associated with the reading activity.

This challenge is rooted in the context model component of RESOLV. The norms and expectations that define an appropriate reading context, including what kinds of supplementary materials are sanctioned, are often tacit rather than explicit (Rouet et al., 2017). In 'real-world' reading contexts, there are many signals related to what auxiliary materials may be appropriate, how to integrate them, and so forth. An LLM lacks both an awareness of what those materials might be and the capacity to express its output in a way that is sensitive to such context (at least by default). Research on genre and disciplinary literacy further underscores that adolescent readers often struggle to recognize and leverage the structural and rhetorical conventions of unfamiliar text types (Shanahan & Shanahan, 2008), a difficulty that AI's often generic and decontextualized output is likely to compound rather than resolve.

Comprehension monitoring is one powerful function for which masterful readers can use generative AI. And in response, they can adapt their reading strategies based on the LLM's output, identifying helpful features, and distinguishing them from incidental ones. When output fails to meet expectations, prompts can be revised to guide the chatbot more effectively. This intentional alignment shows how interaction plays a key role in reading with AI: the chatbot's responses influence how readers approach texts, making awareness of this process essential for achieving reading goals.

For students learning to make use of this technology, recognizing the typical structure and style of chatbot outputs allows readers to give clear guidance to ensure the AI's responses are most useful. This can involve requesting specific focus areas or formal features like simplified or specialized language. For example, a student creating a muscle infographic might instruct the AI to prioritize sources from the current curriculum unless told otherwise. If the student is making the infographic by hand, they can ask the chatbot not to suggest software or structures, helping them better envision their own understanding without predefined formats.

Challenge 3: Iterative Interactive Reading

Unlike traditional texts or websites that remain static regardless of how many questions a reader asks of the text (Leu et al., 2017), reading with generative AI offers a dynamic experience: each prompt yields a new, unique response. Due to stochastic sampling in AI text generation (Ouyang et al., 2025), outputs can differ across runs even when the prompt is the same. This makes it harder to see LLM outputs as the definitive source of knowledge, as they are constantly changing.

RESOLV conceptualizes process decisions as inherently iterative and non-linear, yet the framework assumes that at each iteration the reader can meaningfully update their mental model of both the task and the text. The probabilistic variability of AI outputs disrupts this assumption. Because a second prompt may yield a substantively different response than the first, the reader cannot build cumulatively on prior chatbot contributions in the way they can build on a stable text. Research on multiple document comprehension confirms that adolescent readers already find it difficult to integrate information across sources that differ in format or claims (Bråten et al., 2011); dynamically shifting AI outputs introduce a further integration burden that most adolescents are not yet equipped to manage independently.

A masterful user of generative AI for reading understands that relying on a single chatbot response is insufficient for a full understanding. Adept users synthesize information from multiple sources and interactions, as chatbots lack an underlying model—chatbots, that is, do not "think" about the content they generate (Marcus, 2025; Vafa et al., 2024). Readers must grapple with the tendency of AI to produce internally inconsistent or incoherent—if seemingly articulate—responses over multiple promptings. Remaining aware of their understanding, checking for inconsistencies, and consulting other sources can help. Since LLMs incorporate user feedback, pointing out errors can also improve their future accuracy.

Challenge 4: Contextual Awareness

Generative AI produces text that is responsive to previous interactions, with many LLMs now featuring a history tool that tracks user knowledge and beliefs. For example, if a teacher states that they are using problem-based learning in their instruction this year, the chatbot remembers this and provides tailored suggestions when asked to review a lesson. This feature can track preferences and background characteristics ranging from preferences for writing style (e.g., direct, elaborate) to specific protocols for how writing tasks should be executed (e.g., with a prespecified degree of model autonomy as opposed to requirements for regular human input). But this feature can also lead to unexpected or biased responses, if a learner has revised their understanding separately from their interaction with the chatbot.

In the RESOLV framework, the context model captures the reader's representation of the situation in which reading takes place, including assumptions about what is known and what remains to be learned. When an LLM's memory retains prior assumptions that the student has since revised, there is an effective mismatch between the student's current context model and the one the chatbot is operating with. This problem is not merely technical. Research on the role of prior knowledge in reading comprehension consistently shows that outdated or otherwise erroneous knowledge frameworks impede comprehension (Kendeou & van den Broek, 2007). And an LLM that silently reflects outdated user assumptions can reinforce rather than correct those misconceptions.

Effective users of AI should monitor both their responses and what the chatbot has contributed to ensure that the reader is interacting with a computer that is endowed with *relevant* knowledge. A user can tell the chatbot what to remember or ignore, such as the sources the reader has reviewed, class information, and other details to keep the chatbot's 'knowledge' aligned to the user's context. Lacking a long conversational history and experience with a given chatbot, a newer user of generative AI can benefit from ascertaining what the chatbot remembers about their topic. For example, some models do not by default save user conversation history, simplifying concerns about where the LLM's contributions come from. In contrast, today's frontier models typically apply their knowledge and assumptions about user characteristics by default (Anthropic, 2025; OpenAI, 2025), so giving the chatbot a small amount of information to go on (e.g., one's confidence as a reader, one's knowledge about science, one's skill in athletics) can lead to better-tailored responses about academic texts.

Challenge 5: Knowledge Offloading

Students using AI to produce essays or summaries risk missing out on developing their own knowledge. This is perhaps the most problematic challenge from both an ethical and a cognitive standpoint. While some see AI as helpful for easing the burden of difficult texts (Kosmyna et al., 2025), relying on it to summarize, outline, or interpret complex works means forgoing the valuable effort of active engagement, even if they plan to deepen their understanding afterward.

This challenge maps directly onto the motivational and process-decision components of the RESOLV model. When a student outsources the cognitive effort of comprehension to an LLM, they may not engage in active, goal-directed processing. The concern is well-supported by the cognitive offloading literature, which demonstrates that delegating memory or reasoning demands to external tools reduces the depth of internal encoding (Risko & Gilbert, 2016). For adolescent readers in particular, who are still developing the capacity for self-regulated, strategic reading (Wang et al., 2022), the pull toward AI-assisted shortcuts may be especially strong and its long-term consequences for comprehension skill (e.g., for developing the stamina and processes needed to successfully read challenging texts) especially significant.

Skilled, cautious readers monitor their understanding before, during, and after interacting with AI. Evidence from cognitive science is abundant and clear that exerting effort to recall and apply known information—not to mention integrate into it new information—strengthens memory (Guthrie et al., 1999; Yang et al., 2021). Thus expert readers construct for themselves an explicit model of a topic before engaging AI. This supports continued mastery and clarifies the role the chatbot is meant to play in the interaction (another instance of adopting explicit goals for literacy activities).

To ensure that important knowledge is not offloaded onto the chatbot, students should first articulate what they already know and what they hope to learn—*before* engaging with the chatbot. They should avoid using the AI's output as a substitute for their own understanding and, afterward, clarify what they have learned through reading and chat interactions. These practices are akin to the know-want-learn (KWL) technique, which helps students monitor their progress during a reading activity (Ogle, 1986). One way of translating the RESOLV model into practice, the use of KWL ensures students stay aware of what they knew before and after reading, avoiding the temptation to offload learning onto the chatbot unnoticed.

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Challenge 6: Appearance of Certainty

Generative AI can present information as if it were the unquestionable truth, even when its 'confidence' is low or when it hallucinates sources (Jacob et al., 2025). Although most chatbots will integrate user-identified errors and revise their 'beliefs', they are in no sense aware of those errors until they are called out. A chatbot is unlikely to correct its own errors made earlier in a conversation without explicit user awareness and control, due to limitations in multi-step reasoning.

From a RESOLV perspective, this challenge threatens the reader's ability to build a valid situation model of the text's content, since the AI's confident presentation style may cause readers to incorporate inaccurate information as if it were established fact. The broader sourcing and corroboration literature provides strong empirical grounding for this concern. Studies of adolescent readers engaging with multiple documents show that even skilled students often fail to evaluate the credibility of sources spontaneously, relying instead on surface-level readability as a proxy for accuracy (Bråten et al., 2011).

Expert readers assess source reliability before and during reading. When using AI for support, this requires even greater vigilance—critically evaluating claims, requesting sources, and reviewing sources directly if needed. To prevent students from accepting chatbots' answers as certain, teachers should encourage the solicitation and review of sources, in line with findings from Macedo-Rouet et al. (2013) in traditional reading contexts. Any claims that cannot be independently confirmed should be questioned, and sources should be reviewed for relevance and accuracy. Asking the chatbot about its certainty or for alternative hypotheses may also be helpful, as it can reflect on and evaluate the plausibility of its responses.

Challenge 7: Analytical Superficiality

Generative AI's weak standards of coherence (van den Broek et al., 2015) and limited representations of what the texts they 'read' are about can lead to superficial and often contradictory analytical moves, especially related to more complex topics. Although recent improvements have boosted reasoning accuracy (ChatGPT now performs better on causal and analogical tasks) the model still struggles with multi-hop reasoning (Bang et al., 2023), which requires synthesizing multiple facts. Despite rapid progress, LLMs differ greatly from human reasoning and can mislead readers seeking in-depth analysis of a topic.

In RESOLV terms, analytical superficiality is an obstacle to valid process decisions. If a reader relies on a chatbot to help them determine whether their understanding is deep enough, they are using a tool that may itself lack the standards of coherence by which such depth should be judged. The inferential demands of disciplinary reading, such as in the Muscles activity example, are precisely those that current LLMs handle least reliably (Bang et al., 2023). When reading that collection of texts, a student may not recognize that rereading or other reconsiderations of the texts' contents need to take place, especially when reading with a particular task model in mind.

The LLM may well be no better at identifying what processes need to be carried out to accomplish the reading task.

A masterful reader critically evaluates each step of a chatbot's analysis to identify where its analytic 'skill' falters. If necessary, they attempt corrections but may need to end the interaction due to lack of relevant depth and capacity. Interestingly enough, it is possible to consult with an LLM to ascertain what its current or most prominent analytical limitations are. As of the preparation of this article, for ChatGPT those include causal and counterfactual reasoning, logical proofs, and subject-specific reasoning paradigms such as scientific reasoning, among others (OpenAI, 2025). Being able to recognize when these limitations are relevant to one's reading helps ensure an appropriate level of skepticism or at least critical review when a chatbot is asked, for example, to evaluate alternative explanations for phenotypic variation in muscle development. For some challenges to generative AI's analytical 'skill', a student can explicitly input doubts about a chatbot's analysis to see if it can address them or has hit an analytical limit. The recent introduction of large/deep reasoning models (Wang et al., 2025) has made it easier for users to inspect (some display-friendly version of) the LLM's logic steps, enabling students to evaluate output plausibility themselves or seek teacher guidance.

Strategies to Master the Challenges

Previously we painted a picture in broad strokes about how students can overcome the challenges posed by generative AI use in reading; here we add more detail, covering specific strategies classroom teachers can share with their students and how they address those challenges. Five distinct strategies are highlighted, ordered according to when they could be used during a reading task; to start with an overview, Table 1 maps these strategies onto the challenges that they can best help address:

Table 1
Strategies Adolescents Can Use to Read Purposefully With Generative AI, Aligned With the Challenges They Each Help Address

Challenges	Strategy 1: Start with Explicit Reading Goals	Strategy 2: Use Prompt Engineering Techniques	Strategy 3: Use a Comprehension Monitoring Checklist	Strategy 4: Prompt the Chatbot to Ask Comprehension Questions	Strategy 5: Subject Gist Statements to the LLM's Critique
1: Prompt dependence		✓	✓	✓	
2: Alignment of Text to Context	✓		✓		
3: Iterative Interactive Reading	✓	✓	✓		

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4: Contextual Awareness	✓	✓			
5: Knowledge Offloading			✓	✓	✓
6: Appearance of Certainty			✓		✓
7: Analytical Superficiality		✓		✓	✓

Note. These strategies also map back onto aspects of the RESOLV model, as further described below: strategies 1 and 3 primarily support task-model stability and process-decision accountability, strategy 2 operates at the context-model and process-decision levels, and strategies 4 and 5 reinforce reader ownership of the task model while redirecting chatbot contributions into comprehension-supportive rather than comprehension-substituting roles.

As Table 1 shows, no single strategy addresses every challenge; the five strategies together cover all seven. And importantly, these strategies are not merely general reading practices applied in a new context. Generative AI introduces specific cognitive and epistemic conditions—such as stochastic output variability and fluent but ungrounded text generation—that alter how readers must regulate goals, evaluate information, and construct their understandings of texts. Rather than being simple extensions of existing practices, then, the strategies outlined here are adaptations to these altered conditions.

Strategy 1: Start with Explicit Reading Goals

The purpose a student adopts for reading a text can shape not only how they approach the text but what they learn from it, as the research consistent with the RESOLV model shows (Guthrie et al., 1999). When a student reads with AI, having a specific goal (or goals) in mind for that reading activity can help avoid some of the challenges and pitfalls presented above: a reader can compare what the result of their reading was, relative to what they had first expected to come away with. A reader planning to answer a series of previously viewed comprehension questions can adopt as their goal producing strong answers to those specific questions. A reader expecting to take a position on what they learned from a text and argue for it with peers will need a more complex and sophisticated goal—but nevertheless one that they can meet by understanding what good preparation for that activity looks like.

In RESOLV terms, this strategy stabilizes the task model before AI interaction begins, giving the reader an explicit representation of their reading goal against which the iterative process decisions prompted by chatbot output can be evaluated. This recommendation draws directly on a robust body of research demonstrating that the goals readers set before and during reading function as selection criteria for what information to attend to, encode, and retain (Guthrie et al., 1999). Goal-setting is also a well-established component of effective self-regulated learning. Learners who articulate specific, proximal goals before engaging in a task are likely to have greater strategy use, deeper processing, and superior transfer compared to those who approach tasks with vague or absent goals (Zimmerman, 2002). In the context of reading with AI, explicit goal-setting additionally provides a stable anchor against which students can evaluate AI outputs, reducing the risk that they accept whatever the chatbot provides as intrinsically relevant to the task.

Several specific strategies can support the careful and useful statement of goals in the context of reading with generative AI. A reader-focused version of the RAFT heuristic can work here, aimed at a target literacy product (e.g., the infographic for the *Muscles* texts, a class-wide debate, or an explanatory essay). In this case, students would identify their role as reader (e.g., a critical consumer, a policymaker), the audience for the target product (e.g., their classmates, an expert panel), the format of the target product (e.g., a multimedia infographic), and the topic (e.g., managing the complexity of information about phenotypes as well as muscle-specific facts). Or, if reading texts alongside an LLM without a specific target task in mind, taking a cue from the RESOLV model a reader can identify the 'problem' they are out to solve by reading, whether finding an answer to a specific question or learning about a new topic.

Strategy 2: Use Prompt Engineering Techniques

Prompt engineering techniques include several helpful approaches to crafting prompts that will optimize the output of generative AI chatbots. Guidelines for selecting and implementing these strategies abound (Giray, 2023; Park & Choo, 2024; White et al., 2023). Prompt engineering is powerful because even though we use natural language to interact with chatbots, their underlying computational architecture responds better to our queries when we structure them in specific ways. Several available strategies are especially powerful to support students' use of generative AI to comprehend texts, including:

- Flipped interaction (White et al., 2023), directing the LLM to ask questions of the user (more on this in the final two strategies in this section)
- Chain of thought (COT) prompting (Wei et al., 2022), providing intermediate reasoning steps to maximize the chances that an LLM will yield an expected answer
- Normative interaction, setting ground rules for what kinds of contributions the chatbot should and should not make

These prompt engineering approaches operate on different RESOLV components. Flipped interaction and chain-of-thought prompting primarily support iterative process decisions by making the chatbot's reasoning inspectable across turns. Normative interaction, on the other hand, functions at the context-model level by fixing in advance what the chatbot is and is not authorized to contribute. There are dramatic differences in the kind of reading support that each of these approaches would provide for even a collection of texts as simple as the one found in our *Muscles* example. For instance, a flipped interaction could involve instructing the LLM to ask the reader questions about how the different texts in the collection contribute to their reasoning about how to develop the final infographic. In response, the reader would need to return to the texts, articulate their thinking (in voice or typed interactions), and address any follow-up questions the chatbot presented—which could help the reader deepen their understanding as well as their confidence in their interpretations. If this type of strategy seems too daunting to entertain with a full curricular activity or unit, smaller exposures may also be beneficial. Teaching students to test out the strategies in the context of reading simpler texts, even before diving into a target task like *Muscles*, can help them develop the skills to recognize when to use a given strategy.

Strategy 3: Use a Comprehension Self-Monitoring Checklist

The rationale for using self-monitoring checklists when engaging with AI is that checklists and other strategies to monitor one's own reading comprehension have been shown to be valuable comprehension tools across reading contexts (Vaughn et al., 2022). But they may be even more crucial when reading with AI because of what the alternative represents. Within RESOLV, comprehension monitoring is what keeps the reader's process decisions accountable to their task model; the checklist externalizes this monitoring function, which is especially consequential when reading with AI because the chatbot provides no such accountability on its own. A student who is not monitoring comprehension while reading a traditional text, and without any LLM engagement, may come away with a superficial or inconsistent understanding of that text. But a student who

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fails to monitor their comprehension while reading with generative AI can fall into any number of traps, such as introducing inapt prompts, developing misplaced confidence in their knowledge due to the chatbot's contributions, or failing to think critically to understand what the text is about (Lee et al., 2025). Comprehension self-monitoring checklists that work for adolescents reading in traditional settings can also work here, helping students keep up with what they have and have not understood from a text, and where they need to go next. A sample checklist that has been customized for readers working with generative AI is presented in Figure 2.

Figure 2
Sample Comprehension Monitoring Checklist Adolescent Readers Can Use to Guide Their Reading With Generative AI

Before Reading with AI	**While Reading with AI**	**After Reading with AI**
❑ I know what I am supposed to read, and I understand what I need to do with the text(s). ❑ I have a specific goal for reading. ❑ I have a plan for using generative AI to support my reading, including what I am planning to use it for and when. ❑ I have crafted an initial prompt that is aligned with my reading goal, which I will input into the AI.	❑ I have compared the way the AI describes the content of my text(s) directly with the text(s). ❑ I have independently confirmed each claim made by the AI that does not appear in the text(s). ❑ I have checked with my teacher and/or classmates whenever the AI issued a confusing response. ❑ I have rephrased the responses produced by the AI to confirm for myself I have understood them. ❑ I have submitted my rephrased responses to the AI to check my understanding. ❑ I have consistently returned to the original text(s) to judge their content against the goal I have adopted for my reading.	❑ I can state with confidence that I have achieved my reading goal. ❑ I can explain to my teacher and/or classmates what it looks like to have achieved my reading goal and how I got there. ❑ I understand the role that the AI played in my work to achieve my reading goal.

Note. Teachers could reproduce this checklist verbatim or could add space for students to justify each checkmark (e.g., stating their reading goals, writing out their initial prompt).

Strategy 4: Prompt the Chatbot to Ask Comprehension Questions

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Although LLMs cannot truly understand the texts they read, their extensive training data enables them to generate reading comprehension questions using the flipped interaction prompting technique described previously. Additionally, they can evaluate students' responses to these questions. This strategy works across two RESOLV components at once. First, it uses the chatbot to generate the kind of iterative process decisions that a reader working alone would need to initiate on their own: re-engaging the text, identifying relevant information, constructing integrated responses. But second, it also preserves the reader's ownership of the task model by positioning the LLM as questioner rather than answerer. The theoretical warrant for this strategy lies in the well-documented benefits of elaborative questioning for comprehension and memory consolidation. Generating answers to text-based questions requires readers to re-engage with the text, identify relevant information, and construct integrated responses (Davey & McBride, 1986). Further, reciprocal teaching, in which students practice generating, clarifying, and answering questions about texts, has a robust evidence base in adolescent literacy research (Palincsar & Brown, 1984). The use of AI as a questioning partner can be understood as a variation of that well-established model.

To optimize the usefulness of this strategy, teachers can consider creating custom GPTs (building on existing generative pre-trained transformers). With this tool, teachers can use the natural language interface of OpenAI's ChatGPT to build a chatbot with custom types of interactions, knowledge sources, and limitations. For example, a teacher working with the *Muscles* texts could tell the custom GPT to:

1) Focus on synthesis across the texts;
2) Ensure that comprehension questions address the texts' multimedia features and genre differences, or;
3) Help students cement their comprehension by discussing the texts from the point of view of different readers.

And using a flipped interaction prompting technique can do more than just spur the LLM to ask relevant reading comprehension questions. Students can also provide an instruction to stop asking questions once their comprehension goal is met (e.g., "Tell me when you think I have understood the readings deeply."), thereby helping them cultivate their metacognitive skills about their own reading comprehension.

Strategy 5: Subject Gist Statements (or Richer Interpretations) to the LLM's Critique

While an LLM does not interpret texts in the same way we do (because fundamentally it is relying on pattern recognition algorithms that are not analogous to human cognitive processes), it is nevertheless capable of critiquing our interpretations. In RESOLV terms, this strategy converts the chatbot from a source of content into a probe on the reader's situation model, which is why it should come after independent comprehension rather than before: the student's own understanding of the text is the object of inquiry, and the LLM's role is to subject that understanding to critical scrutiny and inferential pressure. The theoretical basis for this strategy is from research demonstrating that externalizing and explaining one's understanding, sometimes called self-

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explanation, is an effective strategy for improving comprehension (McNamara, 2004). Submitting a gist statement or interpretation to an AI is an example of self-explanation.

After reading, an individual can present their interpretation to the LLM for evaluation of the accuracy and depth. Furthermore, many chatbots also offer voice interaction, mimicking a natural conversation. Sharing an interpretation of a text this way and engaging the LLM in a discussion to help hone a reader's understanding is a valuable strategy for adolescent readers who have done the hard work of comprehending a text and can benefit from a more sophisticated conversation partner (whether in text or speech) to examine their understanding. This sort of exercise can also be used as practice before students engage in similar critiques amongst themselves, in pairs or small groups; such practice with a virtual interlocutor is especially helpful for students with weaker language or reading skills.

Looking Ahead

As LLMs continue to improve in quality and expand in adoption, teachers of adolescent readers will inevitably face questions about how much use of generative AI to permit of their students—or to encourage in them. Certainly commentators on the consequences of the increasing pervasiveness of generative AI have swung to one of two poles: Some argue that LLM use has spread so quickly, and its impact has already been so great, that the wisest course of action is to fully engage with it, in as many contexts as possible, to avoid being left behind (Cardon et al., 2023). Others instead contend that the risks (to individual learning and cognition, to collective creativity, etc.) of relying on generative AI for a wide range of human activities are dire, and that generative AI use should be avoided except for the most circumscribed tasks (Bond, 2025). And while that swing may be tempting—fully embracing generative AI, or fully shunning it—we agree with Kalantzis and Cope (2025) that neither of those 'principled' positions is realistic in 2026.

What the strategies outlined here point toward collectively is a conception of what generative AI can offer adolescent readers when it is engaged deliberately. An LLM used without an explicit reading goal could pull the task model toward whatever the chatbot happens to produce; an LLM engaged after the reader has articulated their goal can instead serve to elaborate, question, or stress-test that goal without displacing it. An LLM used as a source of authoritative content is often a liability, given the concerns we have raised about fluent but ungrounded output; the same LLM used as a questioning partner (Strategy 4) or as a critic of the reader's own gist (Strategy 5) can become a form of always-available "cognitive company." That is, a chatbot can serve as a responsive interlocutor of the sort that has historically been available only where a patient teacher, a study partner, or a well-prepared parent happened to be on hand. Ultimately, the difference between deleterious and beneficial usage may not be the technology at all, but instead the reader's preparation to engage it.

As such, knowledgeable interaction with LLMs, with an awareness of the consequences their use can have for learning with texts, will set teachers up for success in guiding their students. And it will set students up for success in using this fast-evolving technology as they read for the many purposes they may adopt, through their schooling, in their eventual professions, and throughout their lives. Students will need to have a basic understanding of how generative AI works

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(Annapureddy et al., 2025), so they can grasp its many limitations and the potential effects it may have on their reading comprehension, including catalyzing it or hindering it. At the same time, many adolescents are already developing informal practices for using generative AI to read and compose texts outside of school, but those practices often emphasize efficiency and answer generation (Cardon et al., 2023; Dumin, 2024). This trend underscores the importance of classroom instruction that reorients AI use toward deeper comprehension and reasoning.

The empirical literature that would let us say with confidence which AI-related reading practices improve adolescent reading outcomes, and under what conditions, is still emerging; most of what exists concerns college-age writers (Kosmyna et al., 2025) or AI-generated feedback on student writing (Steiss et al., 2024), rather than adolescent reading comprehension in particular. The strategies offered here are theoretically warranted but await empirical test as a package, and the field would benefit from classroom studies that examine whether and under what conditions they translate into measurable gains in adolescents' reading and learning (as a start, in a scientific problem-solving setting, Clerc et al., 2026).

LLMs may give the appearance of thinking. But, at least for now, only humans develop flexible, comprehensive, and dependable models of the world and the phenomena within it—and reading is among the main activities through which young people learn to do so. It is the charge of today's educators to ensure that this generation of students develops and sustains that empowering capacity, even in a literacy environment that will increasingly entice them to cede it to the machine.

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