

Powerful Learning with Emerging Technology

November 2025

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Suggested Citation

Mills, K.*, Noakes, S.*, Pattenhouse, M.*, Shell, A.*, & Vollavanh, A. (2025, November). *Powerful Learning with Emerging Technology*. Digital Promise. <https://doi.org/10.51388/20.500.12265/274>

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Introduction

Emerging technologies have immense potential to promote powerful learning by fostering agency, purpose, curiosity, and connection while empowering learners with skills that prepare them for the future (Digital Promise, 2025b). This paper and the accompanying framework provide guidance to developers, educators, and learners for creating powerful learning experiences with emerging technologies. This guidance **addresses the challenges that developers, learners, and educators experience when designing and implementing emerging technologies for powerful teaching and learning**, both in and outside of traditional classroom settings.

Each role across this ecosystem needs to consider how emerging technologies can enhance human connections that are foundational motivators of purpose, perseverance, and powerful learning. Developers need to design emerging technologies that promote skills and knowledge of learners in classrooms, at home, and throughout communities. Learners across ages and abilities need to make informed decisions about if, when, and how to leverage emerging technologies to support specific learning goals. Educators need to use emerging technologies in ways that enhance learning and prepare learners for their futures.



"The future of learning is about more than just technology—it's about bringing together research, practice, and innovation to create opportunities for every student. AI has the potential to unlock new ways of thinking, create more equitable learning environments, and help every student reach their full potential. As a district, we are committed to using AI in ways that are ethical, transparent, and student-centered, ensuring that every learner has the tools they need to succeed in an ever-changing world."

- Mario J. Andrade, Ed.D., Superintendent, Nashua School District

In this paper, we elaborate three key principles of designing powerful learning experiences with emerging technology.

1. **Evidence-Based:** Emerging technologies should be informed by education research, leveraging meaningful measures of learning, and developed through partnerships with people who have relevant expertise, including subject matter experts as well as educators and learners.
2. **Learner-Centered:** Emerging technologies should build learners' agency, promote metacognition, and be designed for learner variability and accessibility so that every learner can leverage the tool to support their learning.
3. **Skill-Building:** Emerging technologies should support learners in building durable human skills (critical thinking, creativity, and collaboration) alongside content to prepare learners to thrive in our future world.

We synthesized research and practice into strategies to help developers and educators design and implement emerging technologies to promote powerful learning. Practices provide guidelines about how to promote each principle, while strategies offer actionable recommendations to align the design or implementation of emerging technologies to each practice.

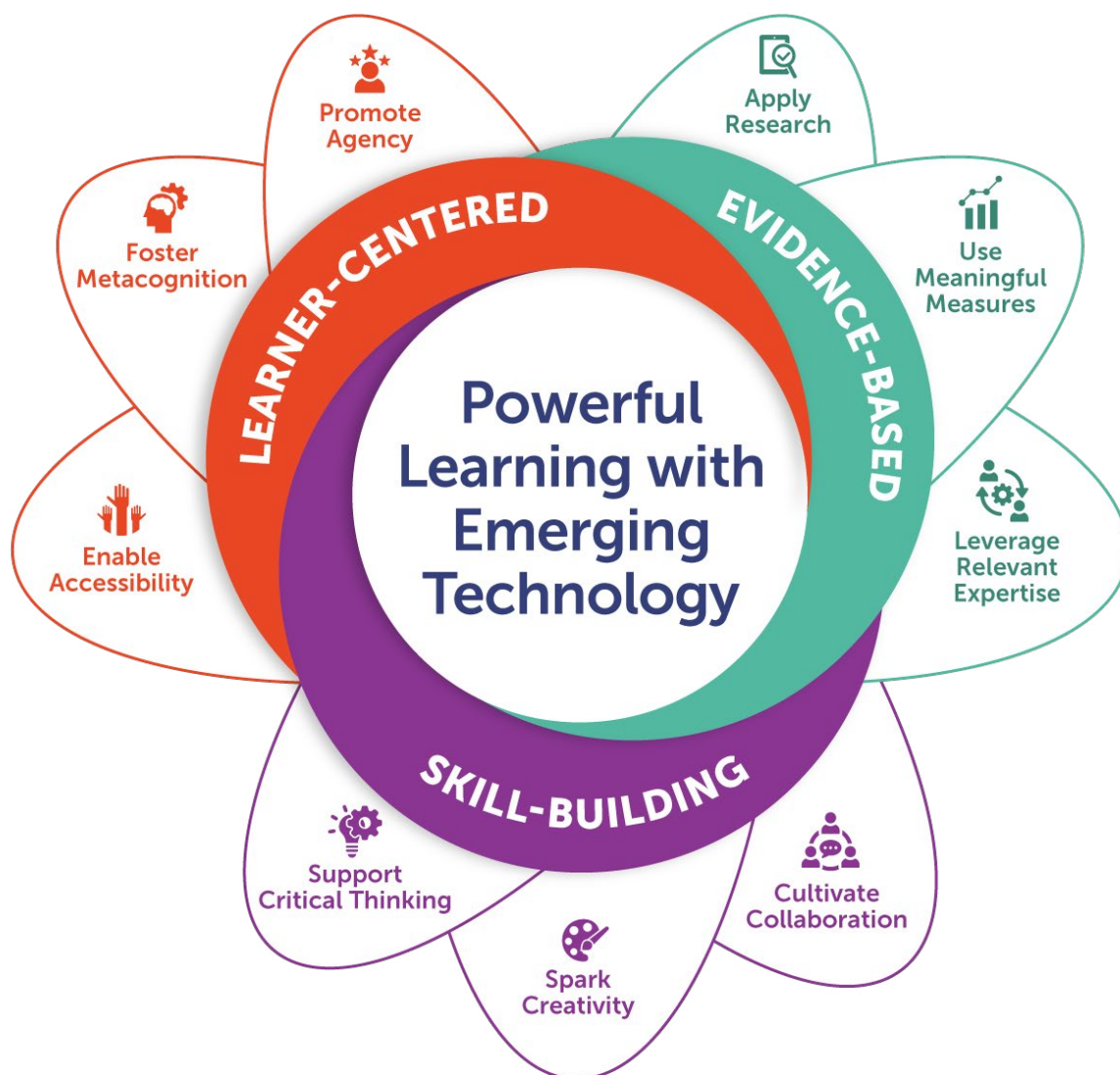


Table 1. Powerful Learning with Emerging Technologies Framework Overview

Principle	Practice	Strategy
Evidence-Based	 Apply Research	Leverage learning theories
		Integrate research-based instructional practices
	 Use Meaningful Measures	Define learning outcomes
		Plan for iterative product improvements
	 Leverage Relevant Expertise	Collaborate with experts throughout development
		Co-design with educators and learners
Learner-Centered	 Promote Agency	Personalize for learners
		Make learning relevant
		Ground in purpose
		<i>Safety spotlight:</i> Privacy
	 Foster Metacognition	Enable productive struggle
		Provide reflective opportunities
		<i>Safety spotlight:</i> Explainability
	 Enable Accessibility	Include assistive technologies
		Consider multimodality
		Allow for translanguaging
		<i>Safety spotlight:</i> Fairness
Skill-Building	 Support Critical Thinking	Foster inquiry
		Promote learner's understanding of emerging technologies
		Encourage evaluation of emerging technologies
	 Spark Creativity	Elevate the human creative process
		Scaffold creativity
	 Cultivate Collaboration	Create opportunities for human connection
		Facilitate collaborative efforts

We advocate for product development teams to engage with the recommendations within this paper throughout the design process. Similarly, we advocate for education leaders and educators to leverage these principles when designing learning environments that integrate emerging technologies and for learners to use these principles when evaluating tools to support their learning. By embedding these principles throughout product design, selection, and implementation, we aim to create a foundation that enables all learners to reach their full potential.

The following sections of this paper outline the principles, practices, and strategies to design and implement emerging technology for powerful learning. Illustrative examples of tools and ideas from the expert interviews are shared throughout this paper. At times, their insights serve as caution signs, with the many unknowns associated with emerging technologies. At other times, their enthusiasm calls for more innovations so that the learning experiences mediated by emerging technologies prepare learners with the skills they need now and in the future. Ultimately, this paper serves as a resource to guide the development of emerging technologies to promote powerful learning now and in the future.

Evidence-Based

Emerging technologies, like generative AI (GenAI), provide an opportunity to apply insights from educational research in new and exciting ways. Emerging technology-enabled learning tools are **evidence-based** when development teams apply data and research findings to inform the design, implementation, and iterative improvements of emerging technologies. We offer developers three practices elaborated with illustrative examples to design evidence-based tools:

- **Apply research**, and demonstrate how the tool's rationale is connected to education research.
- **Use meaningful measures of learning** to continuously investigate the impact of the tool on learners' understanding, application, or transfer of skills or knowledge.
- **Leverage relevant expertise** so products are designed in partnership with a multidisciplinary team of subject matter experts and through co-design with intended users.

Throughout this section, we provide illustrative examples of tools that have integrated these practices throughout the development process.

"You can't brute force AI into the classroom and expect it to work."

- Sara Kloek, Vice President of Education and
Children's Policy at SIIA

Apply Research

Emerging technologies should extend and deepen pedagogy, which entails integrating and applying theories about how people learn. People have designed and implemented learning technologies through computers and the internet for decades. GenAI is a recent innovation in an evolving field of emerging technologies that may provide an opportunity to apply learning sciences in new and exciting ways.

Leverage Learning Theories

Theories about how people learn should drive the design of emerging technologies that aim to support learning, **the ways in which they are implemented into learning environments, and the metrics identified to evaluate their efficacy.** Educational research over the past several decades has developed a body of knowledge illustrating the importance of considering research-based approaches to learning (NASEM, 2018). Examples of learning theories include Dewey's experiential learning (1916), Piaget's constructivist learning model (1952), Vygotsky's social constructivism (1978), Bandura's social cognitive theory (1986), and Papert's constructionism (2020), which mutually reinforce that learning is actively constructed based on experiences and in connection with other humans. Technology that adopts these lenses requires that learning environments promote learner agency, open-ended problems, and human connection (Resnick, 2023). These are only some of many theories of learning that have implications for the design and implementation of emerging technologies.

Integrate Research-Based Instructional Practices

Instructional models from specific subject areas can provide developers with research-based frameworks and practices for skill development to support subject-area learning. For instance, in math, research has demonstrated the value of sequencing math learning from concrete (e.g., a physical manipulative), to representational (e.g., a picture to represent), to abstract (bringing in numbers or mathematical symbols) (Witzel, 2005). For literacy, frameworks grounded in the science of reading demonstrate the interconnectedness of reading skills that are each critical to literacy success, including background knowledge, phonemic awareness, decoding, fluency, and comprehension (Duke & Cartwright, 2021; Scarborough et al., 2009). Instructional resources, such as the Illustrative Mathematics and OpenSciEd curriculum, can guide developers in designing emerging technologies that effectively support learning.

"If you want to produce student growth, go look at what the research says works, and then go implement those things that work. We have to place our bets on the things that will actually help kids learn based on the best evidence we have."

- Ran Liu, Vice President and Chief AI Scientist, Amira Learning

Developers should communicate the research basis for their products with current and potential users. They can do this through a variety of techniques, including a logic model (Figure 1), theory of change or theory of action, or a foundational paper. Highlighting the research basis enables users to have a stronger understanding of the product design and the impact it intends to have on learning.

Amira Is An AI Tutor Designed With Reading Research

Using advanced speech recognition and natural language processing technology, [Amira](#) listens to students read aloud, identifies reading challenges, and delivers micro-interventions based on reading and neuroscience research. To describe the foundational research and theory of change, they developed this logic model in partnership with Instructure. Additionally, Amira has successfully led [three ESSA-aligned studies](#) to understand the tool's impact on learning.



Problem Statement: Teachers and families of early elementary school students often do not have resources to address their individual reading needs. Amira's AI-powered reading platform with automated screeners, practice, and embedded assessments, provides teachers and parents with the appropriate tools to identify specific learning needs (including learning difficulties) in a timely manner, engage students in productive struggle through targeted practice, and generate the appropriate reading interventions after assessing students.

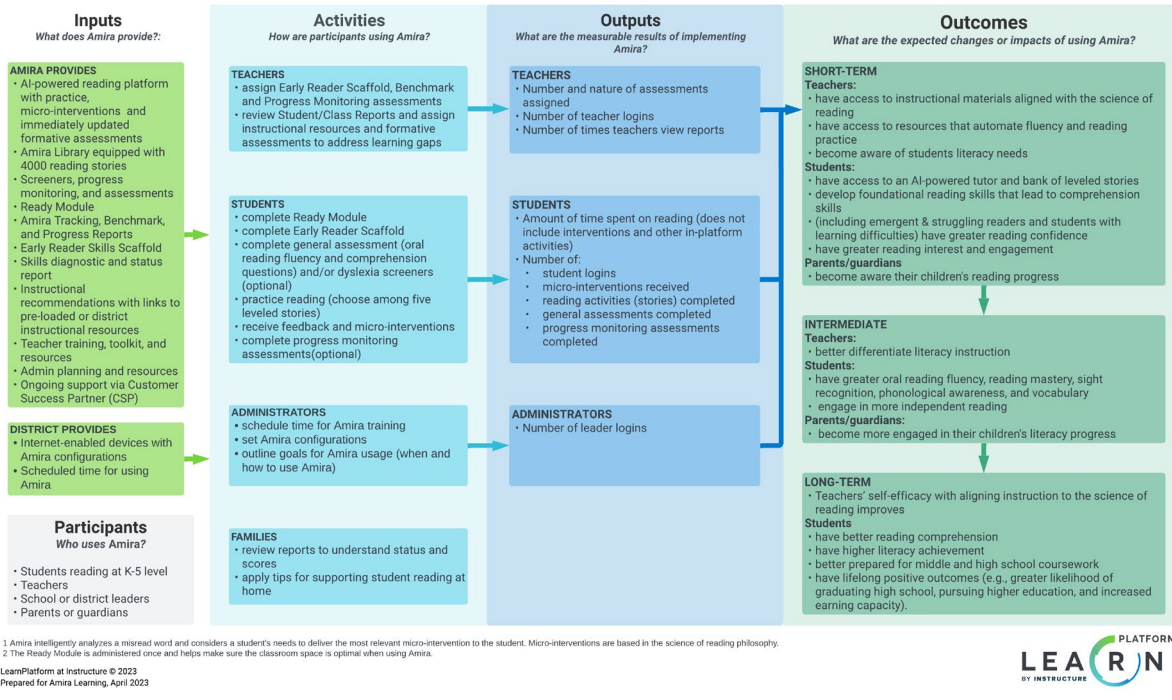


Figure 1. Amira collaborated with Instructure as research partners to ground the theory of change driving the product in relevant research. Source: [Instructure](#).

Educational tools that integrate emerging technologies should be iteratively developed based on current and emerging learning sciences research (Kucirkova et al., 2023). To do this, **we recommend that developers consult with a multidisciplinary team of experts throughout the development process, including learning scientists with relevant technological, pedagogical, and content-area expertise**, elaborated upon in the [Leverage Relevant Expertise](#) section of this paper.

Use Meaningful Measures

Meaningful measures of learning are data points that indicate that a learner has successfully understood, applied, or transferred skills or knowledge from a learning experience. While evidence of efficacy is not unique to emerging technologies, the novelty of these new technologies necessitates the ongoing measurement of learner outcomes to test hypotheses, iteratively improve the tool, and learn more about how these tools impact learning. Because the stakes associated with the achievement of learning outcomes are often high, educators and learners are seeking to understand if and how emerging technology tools demonstrably improve learner outcomes. Moreover, these measurements for outcomes offer insights into where and when the desired outcomes are being supported (Silverman et al., 2024). As detailed in the previous section, **it is critical that developers directly tie these measures to theory and evidence about learning** (Bond et al., 2023).



"AI can accelerate edtech's potential, but our approach to developing high-quality tools must remain the same. We must still prioritize core principles like interoperability, effectiveness, and grounding our product development efforts in learning sciences research."

- Mary Styers, Ph.D., Director of Research, Instructure

Define Learning Outcomes

Measures that are not directly connected to learners' skills and knowledge can evoke positive responses that are not indicative of meaningful learning, such as learners reporting that a product is fun (Huang et al., 2020; Weierich et al., 2010). Many developers rely on user satisfaction measures like in-platform surveys or a Net Promoter Score to understand how well their product is meeting the needs of their users. Another common method for evaluating effectiveness of edtech tools is learning analytics, which typically involves leveraging data from the platform itself. Behavioral measures—logins, content accessed, activities completed, or time on the platform—are used as proxies for more meaningful outcomes, such as knowledge or motivation. However, when the tool aims to improve learning, using satisfaction and usability data in isolation can give misleading perspectives on learner benefit, especially given the novelty of many of these emerging technologies. In fact, the use of these tools may see high levels of engagement but negatively impact learning. For example, the use of emerging technologies based on large language models (LLMs), such as GenAI tools, may interfere with learners' reading comprehension and information retention, even though learners self-report that these tools are helpful for learning (Kreijkes et al., 2025).

Tools that support learning should generate evidence about what students know and are able to do. **We recommend that the efficacy of learning tools is measured by learning outcomes data.** Research-validated assessments provide the most trustworthy means of measuring learner outcomes because they have demonstrated both validity (i.e., accuracy) and reliability (i.e., consistency). However, these assessments can be difficult to access or challenging to obtain results within the desired timeline. Alternative methods of learner outcomes data such as formative assessments or performance data collected through the platform, while less rigorous, can provide more immediate and direct measurement. Other data sources, such as user satisfaction data, platform usage data, or qualitative data about user experience, should be used in conjunction with validated assessments to gain a more comprehensive and nuanced understanding of the learning outcomes.

"If you're using these tools often, I mean, there are times when it's failing 50% of the time to do the thing I want it to do, because it's too complex. It's not there yet, if you will."

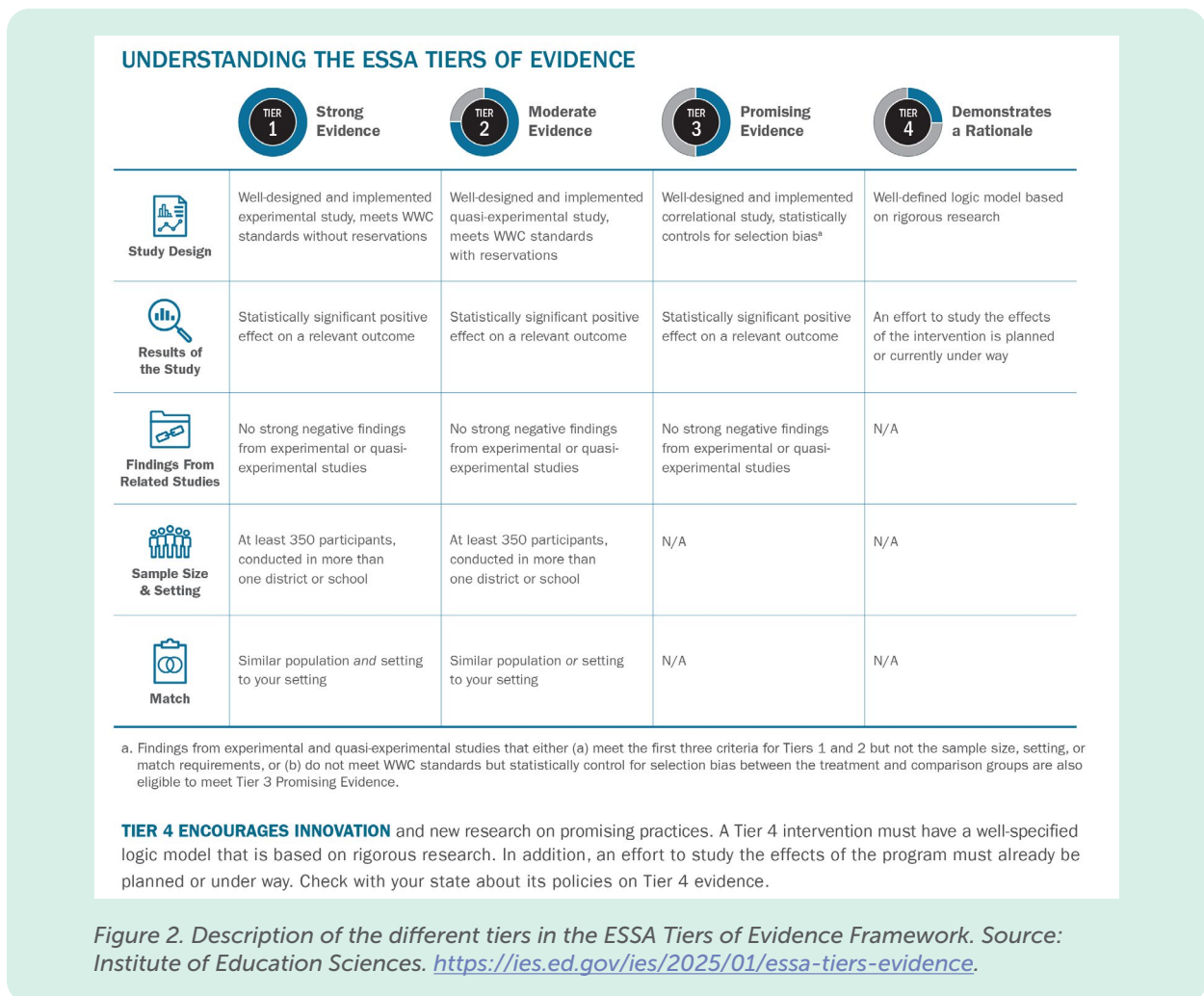
- Pete Just, Project Director for AI, CoSN

Plan for Iterative Improvements

There are a variety of approaches to collect evidence of impact that can be used to iteratively improve emerging technologies. Not all research approaches provide the same level of evidence, and developers investigating learning outcomes should consider which approach best fits their

research questions and resources. Developers can engage with the [ESSA Tiers of Evidence](#) framework as a guide to understand the different approaches. Many education leaders engage with this framework to determine if and how programs, interventions, or tools promote learning (see Figure 2). To achieve an ESSA Tier 4, developers should design products that are **grounded in research about learning**, with a clear rationale that describes this research basis for potential users, as described in the previous section (see Figure 1).

To design a study for product efficacy (ESSA Tiers 1–3), product teams must collect evidence about the impact of the tool on learning. Each tier considers study design, study results, findings from similar studies, sample size and setting, and implementation during the intervention to determine the strength of causal claims between the tool and learner outcomes. Conducting a Tier 1 study will require more time, resources, and participants than Tier 2 or 3 studies. Leveraging relevant expertise, detailed in the following section, can support developers to balance the process of conducting a rigorous research study with the business needs and market pressure to launch and scale products quickly (McGee et al., 2025). Learning outcomes gathered throughout any of the ESSA Tiers of Evidence can provide developer teams with meaningful insights to guide product roadmaps and plans for iterative improvements to the tool.



Leverage Relevant Expertise

Developers of emerging technologies benefit from establishing multidisciplinary teams whose expertise covers the relevant content and context targeted by the learning technology. **Content experts are those who have deep knowledge about the relevant subject area, while context experts hold cultural and community knowledge about those impacted by an intervention.** Leveraging teams of content and context experts throughout the development and implementation process allows the technology to function as effectively as possible.

We recommend two strategies for developers to leverage relevant expertise as part of an iterative development process: (1) Collaborate with experts throughout product design, development, and research of the product, and (2) Co-design with educators and learners. These strategies are detailed in the sections below.



"Product developers need to work with the learning science and instructional design [experts]. A well-integrated team is essential. Make sure you have access to folks who know the science of learning and listen to them, including when you're prioritizing different types of features on your product roadmap."

- Brandon Olszewski, Senior Director of Research, ISTE

Collaborate with Experts Throughout Development

In addition to technology experts, we recommend that the development team includes human development experts, subject matter experts, researchers, and context experts to develop the overall strategy driving product design. The diverse expertise of a cross-sector team ensures accurate translation from research and design to application and implementation in practice. We elaborate on the value-add of each partnership to the development of learning tools that integrate emerging technologies in the sections below.

Human Development Experts

Learners' different developmental stages and learning abilities need to be considered in the design and implementation of emerging technologies, such as AI systems (UNICEF, 2020). AI and its related regulatory policies are typically designed for older users and often lack specific needs and ethical considerations for younger learners (Berson et al., 2025; Chen, 2024). **Having human development experts on the team can help ensure that emerging technology-based tools support the social and emotional maturity, cognitive capacities, and learning needs of their intended users** (Berson et al., 2025; Hirsh-Pasek et al., 2015; Xu et al., 2023).

Subject Matter Experts

Product teams must also collaborate with subject matter experts leading research in relevant areas to stay abreast of cutting-edge developments and ensure accurate translation from research to practice. Most often, empirical, peer-reviewed research in education describes a narrow context and use case. When product teams are expected to extrapolate the findings of a single

study and apply those learnings to the product design, there are significant risks of assumptions or misunderstandings leading to misaligned design. By collaborating directly with research leads in the relevant fields, these experts can support the translation from published studies to design plans to better ensure that research drives products to support meaningful learning. Such collaborations can compensate for the ways that the peer-reviewed publication process often lags behind the rapid pace at which emerging technologies continue to develop. **Collaborating directly with multiple leading researchers with expertise in translating research to practice provides product teams with cutting edge information that can drive rapid design.**

Researchers

Product developers should ensure researchers are collaboratively developing metrics and studies to investigate the impact of the tool. Researchers can support the team in developing rigorous study designs with thoughtful methodologies. Moreover, researchers can support product teams with critical efforts like selecting valid and reliable instruments to measure impact. Once data has been collected, researchers can help with analysis and interpretation to inform next steps for the product.

Pickatale Engages Learners Through Thoughtful Collaboration with Experts

The [Pickatale](#) team aligns product design to cutting edge research through their Transformative Committee, where external partners are engaged to ensure the developers follow existing and emerging learnings about edtech evidence and efficacy, which are then translated into their product design.

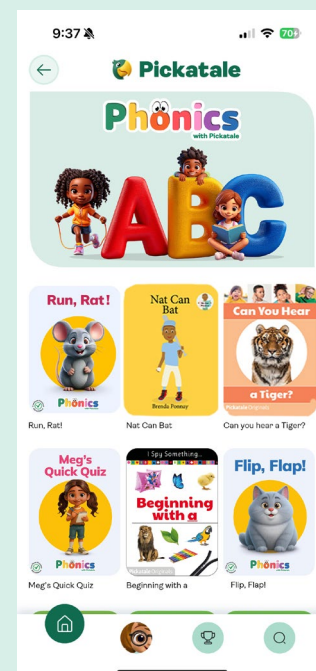
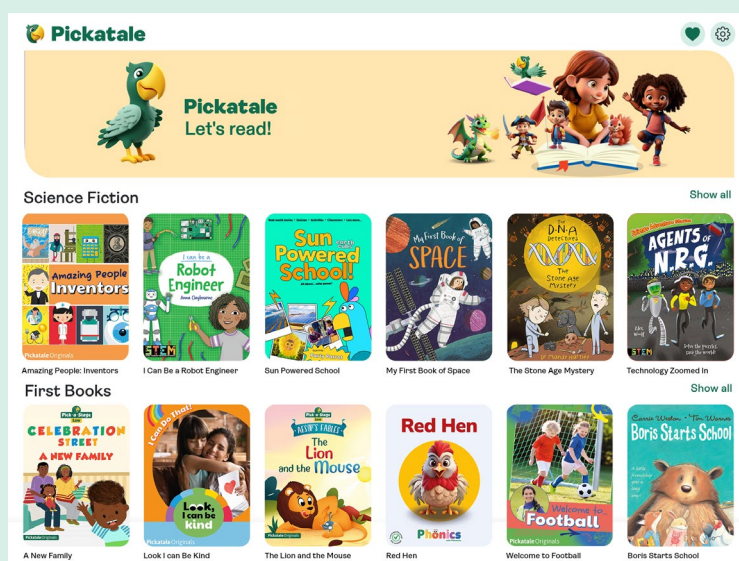


Figure 3. Pickatale's platform which aims to nurture a love of reading for pleasure.

LearnLM Leverages Relevant Expertise To Design for Learning

Learning teams across [Google](#), including Google DeepMind and Google Research, work together to build products, features, and models that provide high-quality learning experiences. Part of ensuring high quality is deep collaboration with learners and educators to continually evaluate, refine and improve the model's performance (LearnLM Team, Google, 2024).

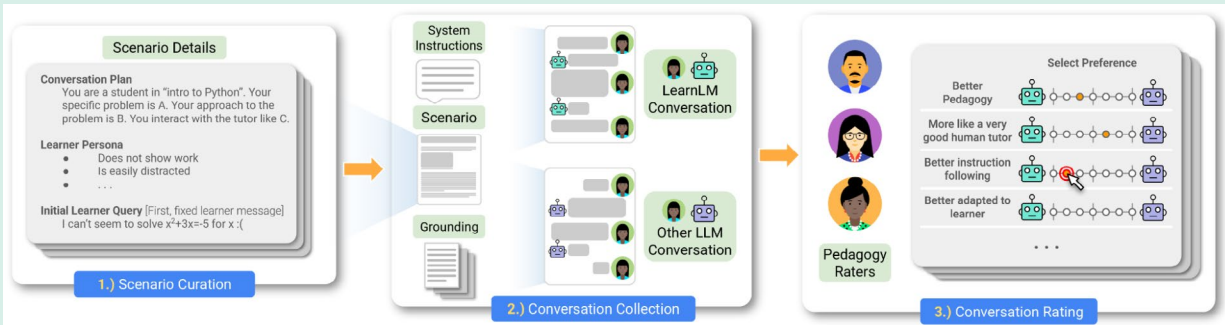


Figure 4. LearnLM's model for designing an LLM that follows pedagogical instructions was iteratively tested and improved with educators and students.

Co-Design with Educators and Learners



"In my experience, developers often leave educators out of too many conversations, which creates the potential to produce harmful or ineffective tools. As a result, educators often have to retrofit what developers do to meet educators' needs."

- Mary Catherine Reljac, Superintendent,
Fox Chapel Area School District

There are a host of contextual factors that need to be accounted for during the development process to ensure that an emerging technology is effective for learning. In most cases, it is difficult for developers and experts to truly understand all the relevant nuances in all of the contexts in which the technology will be used (Hsu et al., 2022). Therefore, **it is essential for technology development teams to partner with educators and learners**. As context experts for their learning environment, educators and learners provide critical insights and guidance for tool development. Their expertise can inform design decisions that allow the emerging technology tool to create powerful learning experiences within the realities of the classroom. Developers should build emerging technologies-enabled tools hand-in-hand with those intended to use the tools—a concept often referred to as **co-design**. Co-design is a process to collaboratively and iteratively design a solution that meets the authentic needs of the intended users in their contexts (University of Delaware Center for Research Use in Education [CRUE], 2022).



"There are times in instructional technology that we actually do kids a disservice in their education because of the assumptions that we make.

[Co-design] helps to mitigate some of those assumptions that are often made inside of designing. It's not just a feedback loop. It's giving the ideas upfront and iterating on them along the way and making sure that the vision meets the practice."

- Bill Bass, Innovation Coordinator,
Parkway School District

The co-design process integrates the insights and perspectives of those who will ultimately use the tool throughout the development process. It often starts with clarity on roles, expectations, and timelines across partners, and then moves into discovery of shared challenges and primary pain points—often through activities like a root cause analysis. Together, co-design partners then ideate and explore potential solutions that could be implemented in a tool to address key needs or concerns. Once prototyped, partners iteratively work together to test and refine the approach before deploying the tool to broader audiences.

"Tool designers need to talk to the teachers and administrators to understand realities on the ground ... If a tool requires students to use headphones, it may present a barrier to use for some schools. Headphones break, students forget to bring them, and schools don't always have the means of ensuring an endless fresh supply."

- Kole Norberg, Senior Learning Engineer at Carnegie Learning

This process helps confirm that tools authentically reflect their needs, goals, and intended use cases in real-world contexts. **It is a particularly important process when integrating emerging technologies** that **draw on existing source material** to ensure that the **voices and perspectives of the intended users** are responsibly represented. Co-design can support these tools to be effective for intended users in specific contexts, which ultimately promotes the efficacy of the tool.

Co-design partnerships create spaces for content and context experts to share insights and perspectives. We recommend developers co-design tools with individuals who represent the diversity of lived experiences across the intended user demographics. Product teams can establish long-standing, trust-based relationships by shifting the power dynamics to elevate each voice in the collaboration, providing fair compensation to participants and formally acknowledging their contributions. Research-Practice-Industry Partnerships (RPIPs) are one approach to co-design. RPIPs bring together cross-sector experts to iteratively inform an edtech product by transforming one-off feedback sessions into ongoing partnerships (Peppler & Schindler, 2021; Digital Promise, 2024). Through this work, educators, researchers, and developers work in cycles to develop, test, and iteratively improve a solution to achieve a high-quality tool for learning.

GIANT Remix is Co-Designed with Teachers, Learners, and Families

The [GIANT Remix](#) team co-designed their tool with students, educators, and families through online bootcamps, in-person workshops, community stations, and school programs. The team worked with public school classrooms over multiple sessions to teach AI literacy to students and educators while gathering input and ideas about the app design and to ensure that the content aligns with the curricula they're actively working through. These efforts supported development of the current product, which embeds learning goals within creative, engaging, and motivating activities for children that forefront human innovation with AI as a tool that brings their ideas to life.



Figure 5. Student signs her comic book created using the GIANT Remix app at the final publication party.

Learner-Centered

Emerging technologies bring new opportunities to design for learner variability by creating learning environments that help students reach their full potential. Learner-centered tools promote agency and metacognition in ways that are accessible for all learners, building upon learners' strengths so that every learner has the opportunity to fully engage, learn, and thrive. The following three practices provide guidance to developers and educators to inform the design of learner-centered tools:

- **Agency** enables learners to pursue knowledge through action, choice, and voice. Emerging technologies can promote agency through features that promote personalization, relevance, purpose and privacy.
- **Metacognition** encourages learners to be active participants of the learning process. Emerging technologies can promote self-regulating metacognition, motivation, and behavior by intentionally designing for productive struggle, reflection, and explainability.
- **Accessibility** removes barriers to learning. Emerging technologies can promote accessibility through features that promote assistive technologies, multimodality, translanguaging and fairness.

Throughout this section, we provide illustrative examples of tools that have integrated these practices throughout the development process.

"If you continue to be left behind slowly, one class after another, that has dire consequences for your future. It may be that you're extremely brilliant, you just don't learn the way the teachers happen to be teaching. I think that one of the greatest promises of AI is the ability to personalize and customize instruction for students and really level the playing field."

- Pete Just, Project Director for AI, COSN

Promote Agency

Learners have agency when they are able to pursue knowledge through action, choice, and voice (Code, 2020; Vander Ark, 2025). Learning environments can promote agency by offering space and support for learners to take initiative and ownership of their learning. Emerging technologies can promote agency with features that:

- **Enable Personalization**, especially customized learning experiences that promote meaningful choice.
- **Increase Relevance**, or connection to their lives and interests.
- **Promote Purpose**, or an opportunity to develop an authentic and meaningful contribution.

Throughout this section, we provide illustrative examples of tools that have integrated these practices throughout the development process.

Personalize for Learners

Personalized learning tailors instruction to the individual, including content, pacing, and assessment. However, personalization alone is not sufficient to design for agency. Personalization promotes agency when learners have opportunities to make meaningful choices about their learning based on their needs or preferences. These customizations support learners by providing insights and recommendations but importantly must also give learners freedom to engage in learning experiences that feel valuable and meaningful to them (Tsai et al., 2019). We do not recommend personalized learning experiences that are overly automated, because providing learners limited opportunities to make informed decisions can detract from agency. Examples of meaningful choices could include how learning happens, where it happens, and what is produced as a result of that learning. Learners' journeys must be driven by choices that are relevant to their own lives and connected to a learner's purpose, concepts that are detailed in the following sections of the paper.

Personalized learning can support scaffolding, promote engagement, and empower learners to take ownership of their learning, fostering agency (Ayeni et al., 2024; Tsai et al., 2019). **Emerging technologies have shown promise at providing features to promote personalization, such as providing customized, real-time feedback or adapting what level of content learners receive based on previous responses.** LLMs have the ability to be adaptive and tailor outputs to an individual, and facilitate the connection of knowledge across disciplines (Anderson et al., 2018; Kirk et al., 2024). This personalization can be designed directly within a tool—for instance, by presenting content relevant to the learner's lived experiences and by providing appropriate scaffolding according to their learning needs—or indirectly by sharing actionable, data-driven recommendations with educators, caregivers, or the learner when appropriate. Each of these features holds promise to provide more customized instruction to learners than can typically be achieved in traditional instruction.

Mentu Supports Teachers to Personalize for Learner Variability

[Mentu](#) supports teachers in making informed instructional choices rather than allowing AI to dictate classroom decisions. Mentu's AI, Shaia, suggests evidence-based strategies, but educators retain agency as the final decision-makers, choosing and adapting strategies to best fit the unique context of their classroom. Shaia then creates a lesson plan that integrates learner variability strategies from the [Learner Variability Navigator](#) and provides an explanation of why each strategy was selected. Strategies have been translated and contextualized for the Latin American context, initially for Colombia.

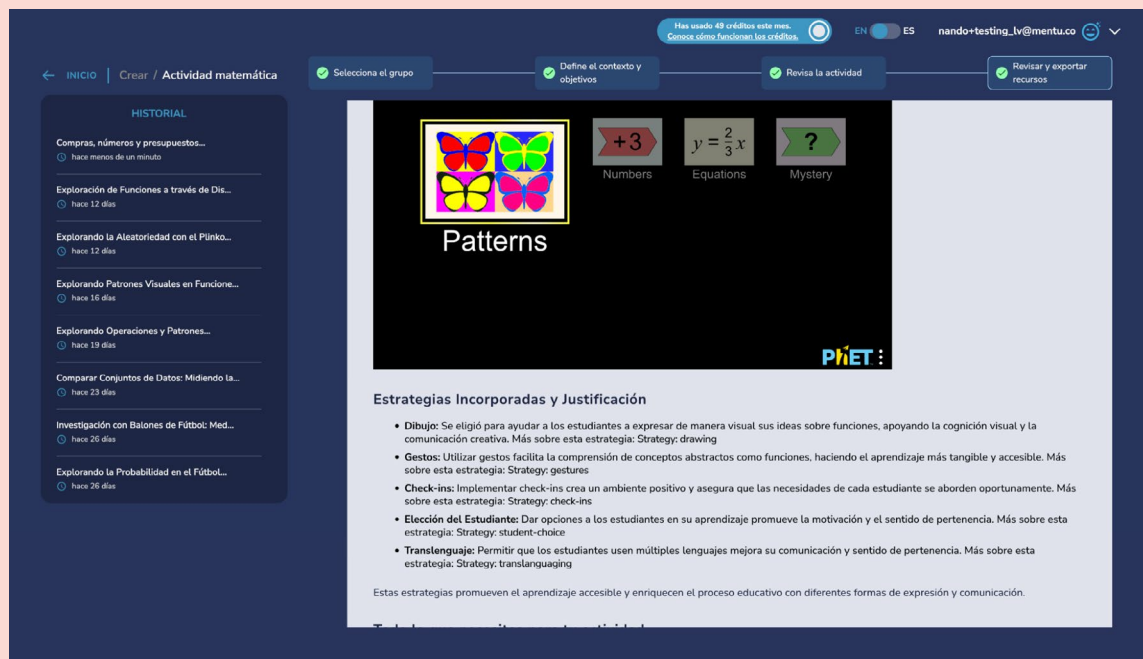


Figure 6. A Mentimeter created lesson plan that has incorporated an educator's selected strategies for supporting learner variability.

Make Learning Relevant

Each learner comes to their educational experience with a unique cultural context, experiences, and a range of background knowledge that shapes their strengths, interests, and areas for growth. Developers can build upon these assets to promote agency that could better equip learners to make meaningful choices, see value within the learning, and apply knowledge and skills across context and through time (Wilson-Lopez et al., 2016).

Acknowledging learners' experiences, personal cultures, and backgrounds—often referred to as funds of knowledge—as a key part of their knowledge base, and bringing this into their learning environment can help learners connect more deeply to their learning and engage in social and civic issues that reflect their interests (Moll et al., 1992). Funds of knowledge can draw upon resources from family, community, peers, and popular culture (Moje et al., 2004). For example, family and community resources could include home language, local events, or landmarks. Peer resources or popular culture resources can include extracurricular activities such as sports, popular movies, and games. Any of these resources could be used to design a more engaging user experience for learning, ultimately supporting learners' motivation and engagement.

There are multiple frameworks developers and educators can leverage to apply funds of knowledge into learning environments that are connected to real-world experiences, including challenge based learning (The Challenge Institute, 2018), connected learning (Ito et al., 2013), and life-relevant learning (Clegg & Kolodner, 2014). Ultimately, these relevant learning experiences support learners to make deeper connections in learning, driving their purpose and ability to apply skills across contexts (Saxe, 1988).

Stemuli Helps Students to Explore Real World Problems and Careers Connected to Their Curriculum

[Stemuli](#) supports students learning and preparing for STEM careers by integrating academic content into an AI-powered video game. Learners discover careers, learn academic and workforce skills, and have fun with their peers in an engaging open world. While they learn, they also get information about jobs where they could apply the skills they're building and what people in those careers typically make. This allows students to build an authentic purpose to their learning by being able to see what opportunities the skills and content they're learning can unlock.

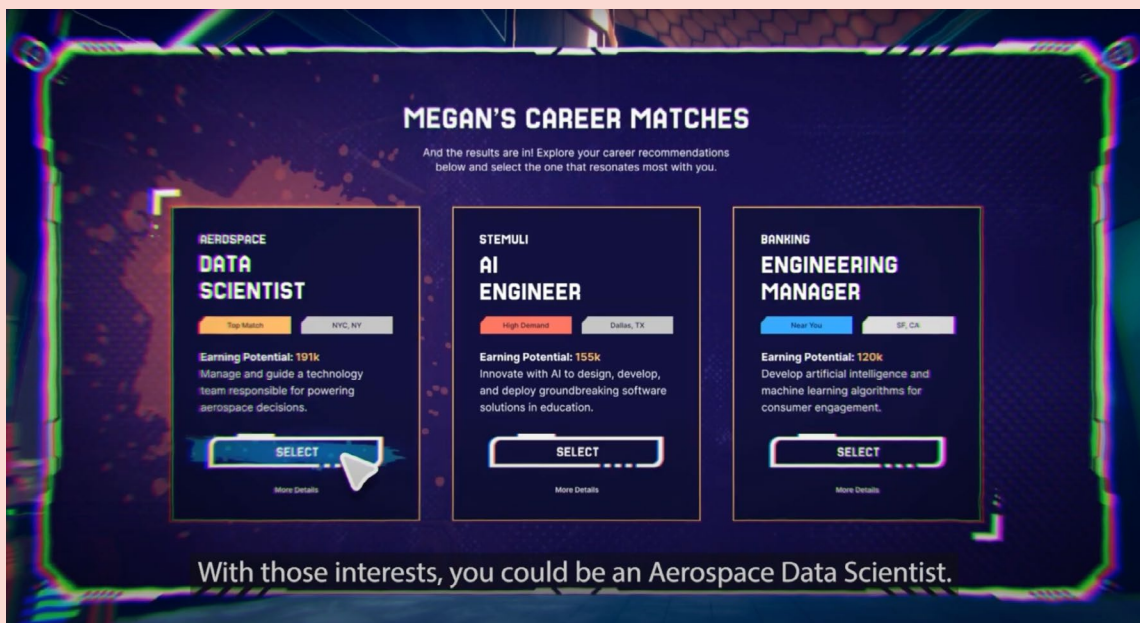


Figure 7. Within the Stemuli game, students can learn about careers that match their interests and skills.

Ground in Purpose

For learners to have agency in their learning, they must also have purpose. **Purpose** is providing learners with the opportunity to develop an authentic and meaningful contribution. Such a purpose can be cultivated by learning designs that align with learners' goals and values and provide opportunities for them to develop solutions to address those challenges. **Having purpose promotes agency because learners understand how their effort on a task is meaningful and aligned to their values and long-term goals** (Anyon et al., 2018). Purpose can also be deeply connected to a civic-mindedness, which involves seeing oneself as a part of a larger community and feeling empowered to make change (Payne et al., 2020).

Human connection is an important driver of purpose (Cantor et al., 2021). Many times, relationships with a parent, peer, or mentor provide the foundation of why learners find purpose in learning. Human connection drives moments of joy, inspiration, and productive struggle, ultimately promoting purposeful learning.

Emerging technologies should be embedded as tools to facilitate experiences that are connected to the values and goals of learners and build meaningful relationships within a learning environment. For example, emerging technologies can promote community connected projects, entrepreneurial experiences, pathways related to workforce skills, and connections between arts, leadership, extracurriculars, and subject-area learning (Vander Ark, 2025).

AI Quests Promote Purpose with Scenarios Based on Real Life Challenges

[AI Quests](#), a collaboration between Stanford Accelerator for Learning and Google Research, enables learners to take the lead in solving problems like preventing flooding at a local market while simultaneously exploring how AI models are built and refined. Quests are specifically designed around the big idea that humans can initiate and design AI applications that can address some of humanity's biggest unsolved challenges.

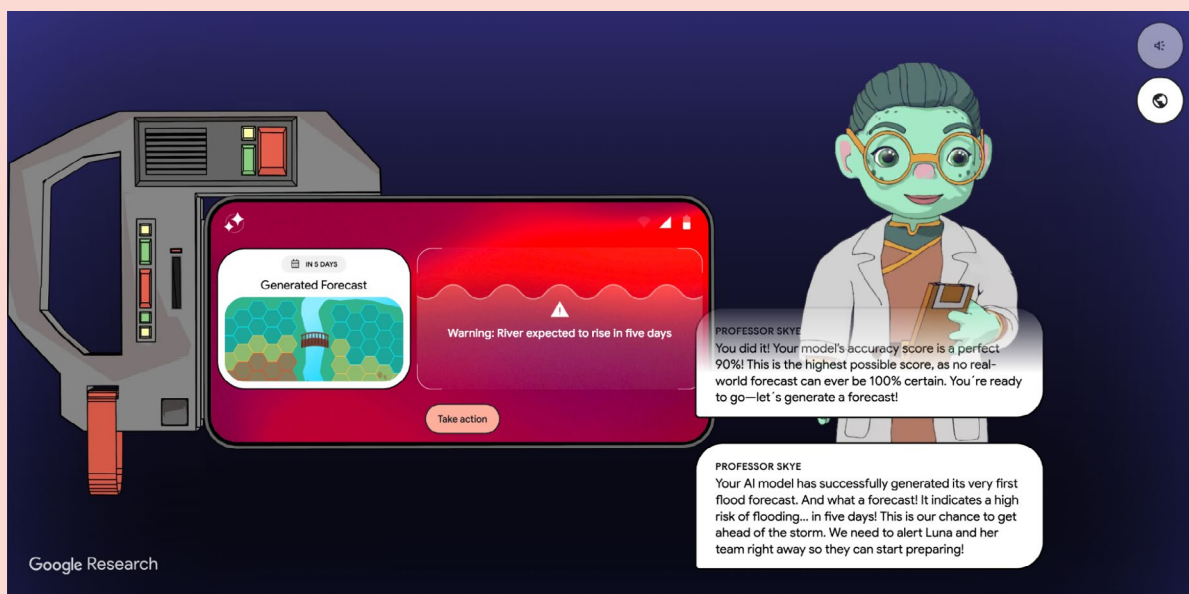


Figure 8. In Market Marshes, learners can select different data sources to predict floods, then test the accuracy of their models and make adjustments to refine them. They can apply those models to real-life scenarios, which builds their purpose for learning (Sacks, 2025).

Safety Spotlight: Privacy

Emerging technologies hold significant potential to differentiate learning experiences in real time by adapting to each learners' needs. However, to develop learner profiles, including the unique strengths and needs of individuals—both academic and social-emotional—requires increased access to learner-level data (Shah & Bender, 2024).

Data and security privacy measures ensure that learner-level data is protected and guarded against unauthorized access ([ISTE, 2024](#)). Development teams can promote data privacy by:

- Adhering to industry standards and laws for secure environments.
- Collecting only the data that is necessary for their purpose.
- Allowing users to understand the data that is collected to the extent that they are able.

SoapBox Labs Limited, trading as AI Labs Curriculum Associates, has been building voice AI specifically for children since 2013. The team has taken measures to ensure their AI is fair, evidence-based, and secure, ensuring learners and educators understand how it works and how their data is used, showing how safety and agency go hand-in-hand. The company [explains](#) clearly to users what information they may collect directly and indirectly, how the data will be used, and how the data is stored.



Figure 9. In 2022, SoapBox Labs earned the first-ever Digital Promise certification for mitigating bias in an AI system.

Foster Metacognition

"I think the important question I have as I look at those platforms is 'Who's doing the thinking?' Or 'how is the student thinking being prompted through the use of AI?' So long as the programming behind that is driven in a way that it promotes critical thinking, creative thinking on the part of the students, while at the same time providing opportunities for collaboration with other students and communication with other students, I think there's a benefit there."

- Julio Vazquez, Director of Instruction and Human Resources,
North Salem Central School District

Metacognitive learners reflect on their own thinking, monitor their thinking and learning strategies, and apply self-regulated learning to adjust their goals based on what is being learned (Baker and Brown 1984; Flavell, 1979). Metacognition is critical for both learning and problem-solving (Güner & Erbay, 2021), and it promotes the development of durable skills such as critical thinking (Rivas et al., 2022) and curiosity (Goupil & Proust, 2023). Learners need metacognitive awareness to support complex decision-making, such as what and how to study or learn next.

Metacognition is a component of self-regulated learning, which encourages learners to be active participants in their own learning (Zimmerman, 1986). Self-regulated learning theory posits that self-direction and self-motivation are interconnected components that drive each other (Zimmerman, 1990). That is, the skill and will of learners cannot be separated from one another. When learners are able to apply their metacognitive skills to reflect upon their thinking, while maintaining motivation and changes to behavior, they become self-regulated learners. (Bandura, 1986; Zimmerman 1990).

Emerging technologies can promote metacognition by allowing for opportunities for productive struggle, encouraging reflection and supporting learners with making adjustments to their learning process.

Enable Productive Struggle

Learning happens best when it is appropriately challenging, creating chances for learners to take risks, make mistakes, and learn from their mistakes. Productive struggle is when learners are able to persevere through this challenge and work toward a solution (Kulesa et al., 2025). When learners work through challenges, they are required to slow down and reflect on their learning process and consider new strategies—key aspects of self-regulated learning. When they successfully navigate challenging learning experiences, they will likely have greater self-efficacy and confidence in future-related tasks.

Emerging technology-enabled personalization features enable content to be adjusted, sequenced, and scaffolded to the appropriate level of challenge. Features can be designed to support learners to adjust behaviors and maintain the motivation needed to navigate a challenge, particularly when paired with human mentorship and support. These features that promote relevance and purpose can motivate learners to persevere through a learning challenge.

“What’s most important is that students are able to see that when they struggle, it’s part of learning and that other people struggle. The ability to see that people don’t just read and understand is something students don’t know. Things that make learning visible and reward it is important. People don’t value that they are learning when they are struggling.”

- Kole Norberg, Senior Learning Engineer, Carnegie Learning

Providing learners with safe spaces to explore new challenges and make mistakes, with opportunities for productive feedback, can support learners in persisting through these challenges.

This foundation promotes the growth mindset that allows learners to see the value of failure in the learning process and to see themselves as capable of driving their own learning (Haimovitz & Dweck, 2017).

Research has found that some GenAI tools can inhibit productive struggle by reducing cognitive effort, such as automating processes that would otherwise require cognitive effort and reflection. Sometimes referred to as “metacognitive laziness,” the effects of using emerging technology tools without prior cognitive effort reduce learners’ ability to activate these key processes (Fan et al., 2024; Gerlich, 2025; Kosmyna et al., 2025). It may also interfere with learners’ ability to reflect on their own knowledge and competencies, which might prevent them from engaging in further exploratory behaviors (Abdelghani et al., 2022). Strategies that support productive struggle when leveraging emerging technology tools include:

- **Use Technology After Effort.** Providing space for learners to bring their own thinking and ideas to the table before bringing in technology supports can allow them to more deeply engage with their own thinking and learning (Kosmyna et al., 2025). For instance, if learners use LLMs to automate writing processes before any initial efforts at sense-making, this can reduce both cognitive effort and ability to reflect upon and modify the automated output to promote sense-making processes and reflection (Kosmyna et al., 2025). On the other hand, when learners have the opportunity to think and work through sense-making before turning to emerging technologies for support, they are better able to consider where and how the technology can improve upon their initial thinking, using it as a partner and enabling deeper reflection.
- **Prioritize Human Relationships.** Human relationships and mentorship within the learning environment also promote productive struggle (Kirschner & Hendrick, 2020). Many emerging technology tools are currently designed for one-on-one device use, with limited opportunity for human connection. While 1:1 technologies efficiently deliver personalized content to students, they are less likely to provide foundational relationships that motivate students to persevere through challenges. Without accounting for relationships or interactions within the learning environment, these tools risk students feeling isolated and disconnected, leading to less engagement and motivation (see Collaboration for more).

ST Math Promotes Productive Struggle with Mastery-Based Progression

[ST Math](#) takes multiple approaches to ensuring that learners are able to engage in productive struggle. Learners work their way through carefully structured sequences of rigorous math content that move from the visual models to incorporating mathematical symbols and language. These scaffolds enable learners to move through the content with a desirable level of difficulty. Learners must master the content to move on, but also receive real-time feedback that helps them adjust their approach and persist.

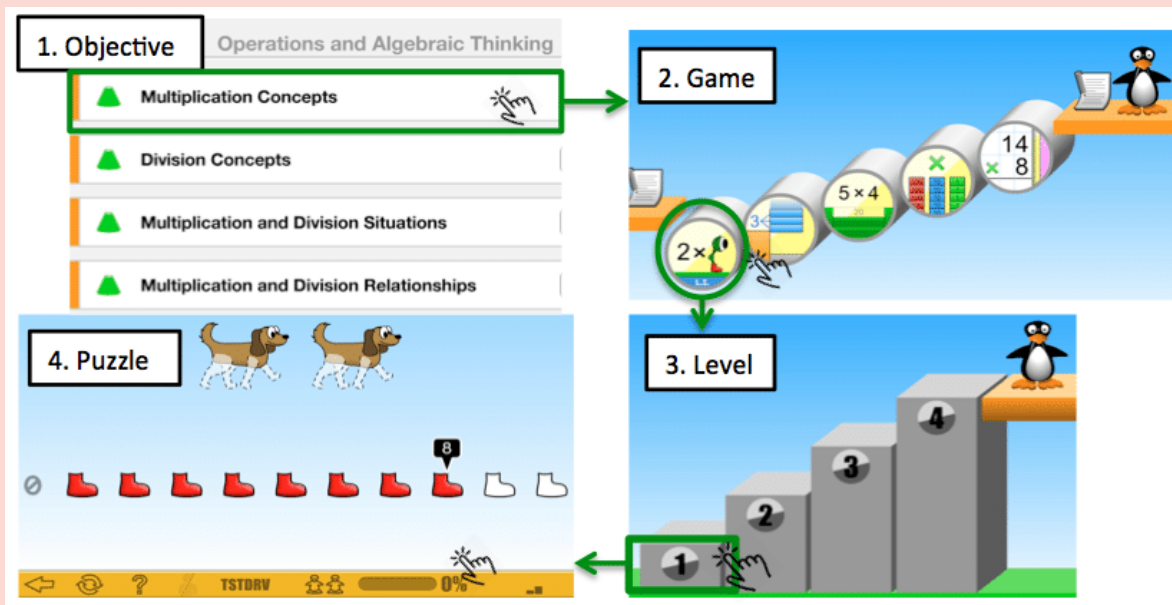


Figure 10. ST Math uses a tiered structure with top level objectives (math concepts), then games (problem solving scenarios), levels (progressing difficulties or puzzle groups), and puzzles (specific questions) to support the right level of productive struggle.

Provide Reflective Opportunities

Reflection supports metacognition and self-regulated learning by encouraging learners to make their thinking visible, evaluate outcomes, and leverage opportunities to adjust their strategies and learning processes to better achieve their goals. The use of emerging technologies have high levels of demands for metacognition, particularly in self-monitoring and controlling one's thought processes (Tankelevitch, 2024). LLMs in particular can provide fast and unrestricted access to knowledge, which can ignite curiosity due to its open and exploratory nature (Abdelghani et al., 2022). However, access to high volumes of information very quickly may interfere with a learner's ability to form an understanding of their information gaps, which are essential for metacognitive awareness, and can interfere with opportunities for self-regulated learning (Ganuthula, 2024).

Emerging technology-enabled tools have ample potential to support this process through creating space and reminders for learners to reflect upon their learning and making their learning process more tangible. Features that could support this process include:

- **Creating opportunities for reflection**, such as leveraging chatbot learning assistants, can encourage a learner at different times to pause and nudge them to think about their own thought process, level of understanding, and strategies to support learning (Yin et al., 2025). This can promote metacognitive processes by encouraging learners to ask questions and to think about missing information (Abdelghani et al., 2022). There is some evidence that adaptive learning technologies can disrupt metacognition and self-regulated learning if they provide too much guidance and evaluate their progress automatically, but they can also be intentionally designed to thoughtfully release responsibility of self-regulation to the learner (Molenaar, 2022). Druga and Ko (2025) provide design recommendations for AI Copilots to support learner agency, such as allowing users to personalize prompts and responses. This can include the extent to which users want AI-enabled support within the platform and the types of responses the agent provides (e.g., “always give me three ideas”), which can allow learners more or less time and space for reflective practices as needed.
- **Learner-facing data reporting**, including text-based feedback, recommendations, visualizations, and dashboards, allows learners to better understand their online behaviors and increases metacognitive awareness of their learning and study needs (Bodily & Verbert, 2017). While learning analytics are often collected on the back end to personalize learning and design learner pathways, learner-facing data enables a learner to reflect on their own learning and to engage in self-regulation to make their own decisions about how to adjust their behaviors and goals as needed. Because monitoring and regulating learning can be a challenging skill, especially when learning new content, developers should consider how they can scaffold self-regulated learning. This scaffolding should involve guidance from mentors and peers (Kirschner & Hendrick, 2020) and may involve a gradual shift from back-end data analytics driving learning pathways to slowly increasing the learner-facing data, creating opportunities for learners to have more agency in their learning (Molenaar, 2022). **Providing opportunities for learners to customize how their data is displayed to suit their learning goals is associated with agency and metacognition and makes feedback more effective**, acknowledging that different users have different needs (Teasley, 2017). It is important that learners have the scaffolds in place to understand and effectively use their data and to also ensure that data is only one aspect of the holistic support and feedback they receive (Hooshyar et al., 2023).

MATHia Makes Data Clear to the Learner to Drive Mastery

[MATHia](#) problems are multistep processes where students engage with a series of interconnected skills and progress through adaptive problem sequences that adjust based on continuously updated skill mastery. Progression to a new skill set is contingent upon mastery of the prior skills. Importantly, students and teachers can see the mastery progress, giving both insight into what a student has mastered and where a student might be struggling.

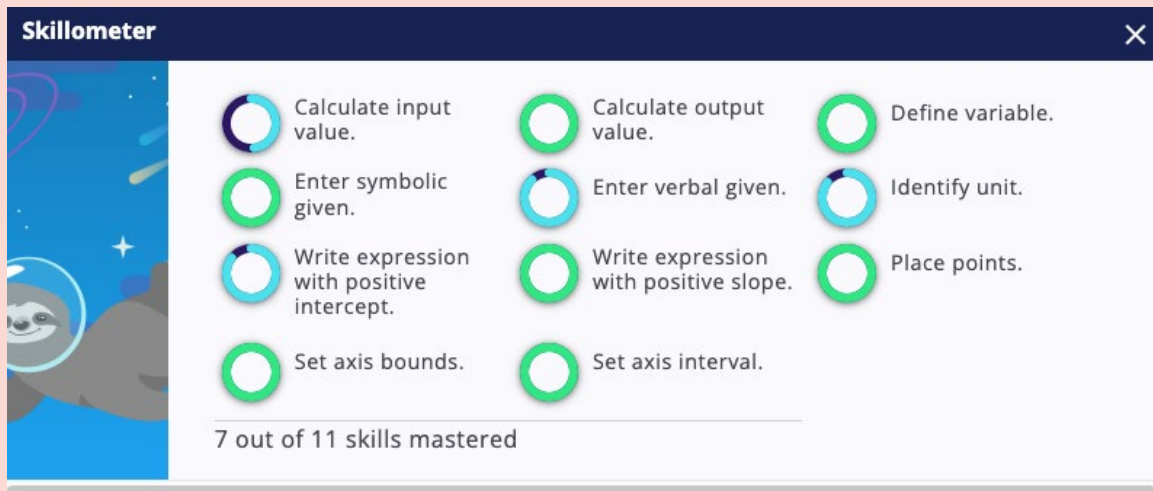


Figure 11. The skillometer shown here shows how this information is communicated to students so they can see the evidence of their learning.

Safety Spotlight: Explainability

Explainability ensures learners understand when and how emerging technology is used within a tool and for what purpose. Explainability can promote metacognition by providing users with the information and opportunity to leverage learning tools to meet their own needs and goals.

Tools can promote explainability by promoting:

- **Communication.** Tools can tell users when emerging technologies are integrated to provide feedback, generate content or make suggestions
- **Customization.** Tools can provide opportunities for learners to customize what and how feedback or data is displayed to suit their needs and learning goals (Druga & Ko, 2025).
- **Usability.** Tools can provide learners with scaffolds to understand how they can apply feedback or data to meet their learning goals

- **Confirmation.** When predictive analytics provide automatic suggestions, tools can support learners to understand how their data was utilized to make predictions, and offer opportunities for them to confirm or adjust the suggested next steps to meet their learning goals.

Journify Learning is an example of a learning tool that promotes explainability. The educator-facing tool clearly labels the use of AI throughout user interactions, including where AI is used to generate content like assessments, worksheets, goals, and suggestions. The tool uses the “🌟AI” label consistently throughout the product to make it easy for users to spot. Moreover, the tool includes an AI warning banner that always stays on the bottom of the user screen to emphasize the important reminder that content must be reviewed and verified by the educator for accuracy and appropriateness.

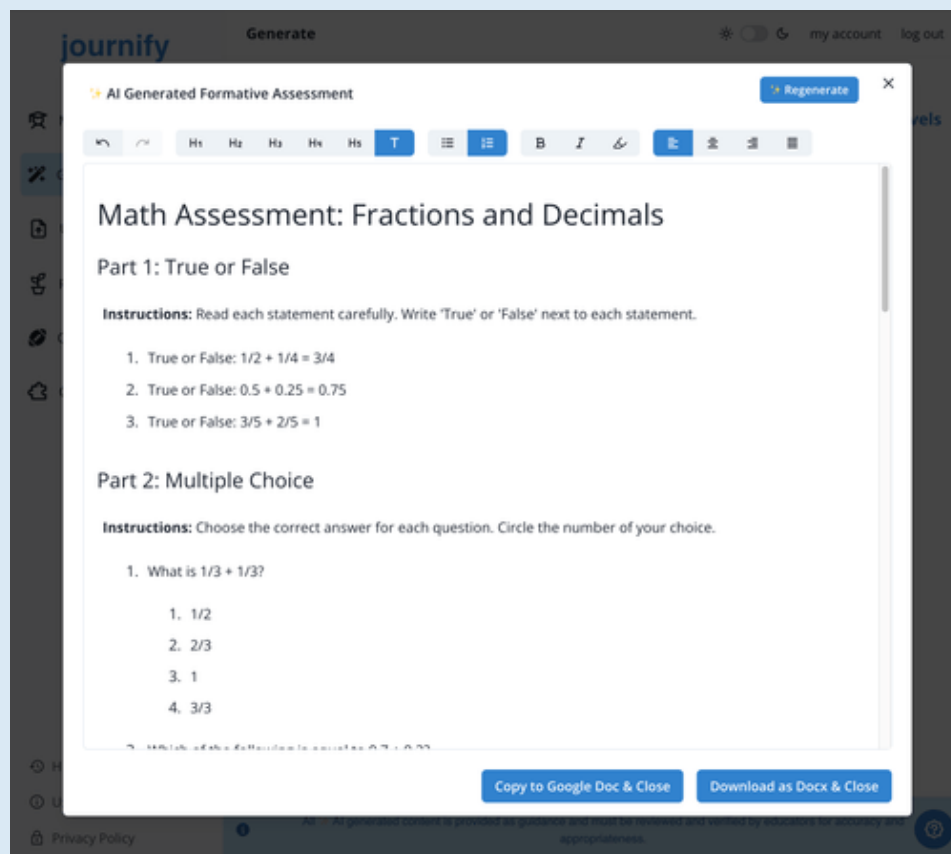


Figure 12. Journify consistently uses the “🌟AI” label to make clear where AI assistance is available, allows users to opt into that support, and ensures educators have the opportunity to review and edit AI outputs before sharing with learners.

Enable Accessibility



"There's a whole spectrum for blind and low vision. So, I think realizing the diversity even within those two terms and then just thinking about all the different types of tools that a person might use is something developers just need to be aware of. It's never just one thing for all needs. The world likes to kind of segregate in all these different categories, but intersectionality is important. I want developers to understand all of those nuances."

- Gina Fugate, Computer Science & Technology Teacher,
Maryland School for the Blind

Many learners bring the motivation, skills, and background knowledge needed to immediately engage in learning, but some experience barriers that prevent them from fully engaging. These kinds of barriers can be wide ranging, from discrete disabilities like dyslexia or dyscalculia to cultural or language barriers. For all students to benefit from digital tools, these tools must be accessible to people with diverse backgrounds and abilities. **When tools for learning are designed with accessibility in mind, all learners can meaningfully participate, navigate, and interact with digital content in ways that are essential in our increasingly digital world.** Every learner deserves access to high-quality learning experiences (CAST, 2024; Ruiz et al., 2022).

To remove barriers to learning, developers can build tools that allow the full spectrum of learners to fully engage in their learning. Universal Design for Learning (UDL) is an inclusive educational design framework grounded in research that supports learners' success by focusing on the design of the learning environment through multiple means of Engagement, Representation, and Expression & Action (CAST, 2024). Emerging technologies can support inclusive practices for all learners by applying the tenets of UDL (Bray et al., 2022) to product features that promote assistance, relevance, and multimodality. **Assistive Technologies** promote UDL tenets by leveraging technology so that learners of all abilities have opportunities to engage in meaningful learning. **Multimodality** promotes UDL tenets representation, action, and expression by enabling flexibility in how ideas are presented and expressed. **Translanguaging** allows for flexible use of language to allow learners to engage with their learning in the most meaningful form. Each of these design features is discussed in more detail in the sections below.

Include Assistive Technologies

The potential for emerging technologies to support learners who have been historically overlooked in product design is particularly strong (Paglialunga & Malogno, 2025; Sennott et al., 2025). For instance, emerging technologies enable closed captioning systems to be translated into multiple languages, including American Sign Language (ASL), in real time. Emerging technologies have the potential to increase access to tools such as text-to-speech, audiobooks, and adjustable text formats. Learners with communication differences can use tools integrated

with emerging technologies to assist them with writing by using text-to-audio and transcription support features, while learners with neurodevelopmental disorders can use wearable AI devices like smartwatches or headbands to monitor physiological signals (e.g., heart rate, brain activity) that provide real-time feedback to help manage their attention, stress levels, and learning state (Shahini et al., 2025; McGee et al., 2025).

Guidance and co-design can support developers to design assistive technologies. Multiple standards such as [WCAG 2.1](#) (Web Content Accessibility Guidelines) and [Section 508](#) have established guidelines to ensure that users with disabilities can access digital content. A Voluntary Product Accessibility Template ([VPAT](#)) can help products to evaluate their accessibility. In addition, as emerging technologies are at the leading edge of providing accessibility, products should also engage in co-design to ensure that learner's barriers to access are thoroughly addressed through the product design.

Be My Eyes Uses Computer Vision to Provide Accessibility

[Be My Eyes](#) allows people who are blind or low vision to access visual information. By leveraging emerging technologies, Be My Eyes helps to translate visual information into text or auditory information. Be My Eyes also enables the user to keep humans in the loop by having the option to connect to a volunteer to understand more about the visual information.

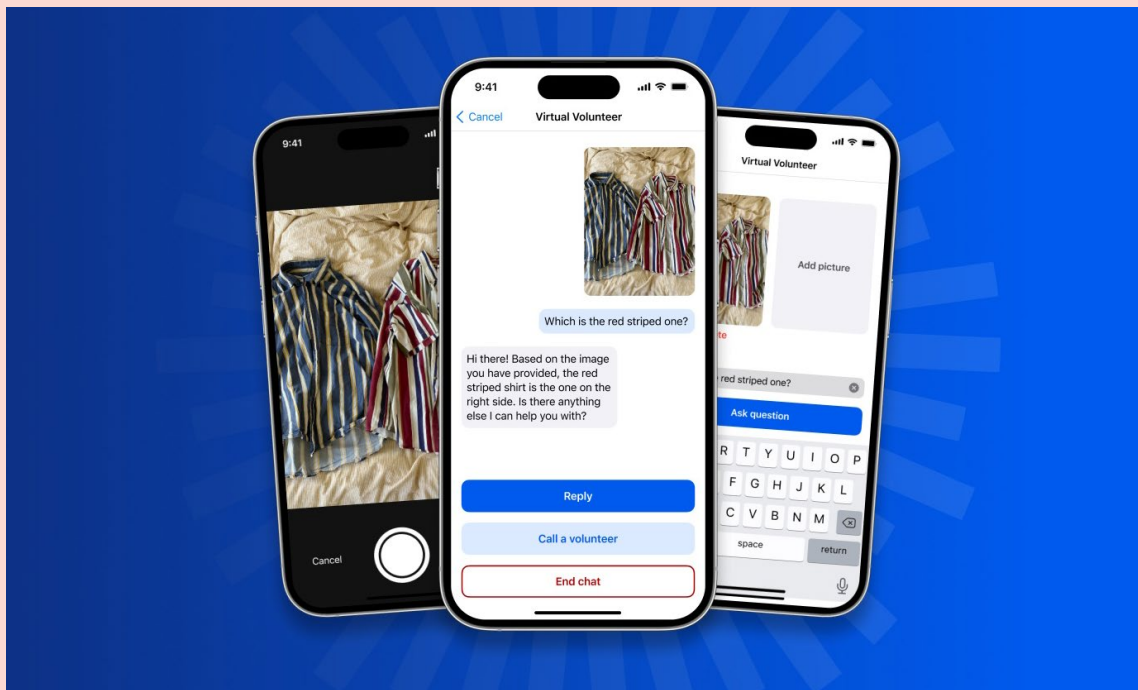


Figure 13. Users can upload a picture and receive a generated response about what is pictured. They can also get connected to a volunteer if they have additional questions or want to verify the generated answer.

Consider Multimodality

A major opportunity for innovation with emerging technologies is the ability to promote **multimodality**, which is when learning and expression can happen across different sensory modalities (e.g., visually through graphics or text, auditorily through speech, physically through movement). Emerging technology-enabled tools have the ability to provide multiple means of representation through generative content and expression through multiple input models.

Emerging technologies have the ability to generate images, text, or video to help students understand concepts. Contrary to the debunked theory that learners have a single learning “style” in which they best take in information, there is ample evidence that learners benefit from multiple forms of representation (Brünken et al., 2004; De Bruyckere et al., 2015). For instance, visual representations—such as drawings, diagrams, graphs, and concept maps—can support learners in processing abstract concepts.

Learners use their working memory to process new information, a key component of learning. Multimodality can support learners in integrating new learning into memory by allowing them to process across both their auditory and visual working memory systems (Tindall-Ford et al., 1997). On the other hand, developers and educators should remain mindful not to overwhelm learners with multiple modes of engagement at the same time, which can impede learners’ limited working memory capacity due to extraneous cognitive load (Sweller, 2010).

These technologies open up a world of possibility to collect multimodal data to provide timely feedback, which has affordances for learning (Hattie & Timperly, 2007). **Emerging technologies can enable students to show their thinking and demonstrate understanding through multiple input models, such as movement, drawing, or recording audio.** Druga and Ko (2025) recommend that AI platforms should allow for multiple input modes (e.g., voice, text) so that learners with different learning needs can select their preferred interaction mode. Through automatic speech recognition (ASR), learners may show their thinking verbally, such as read-alouds on [Amira](#). AI-enabled photo/document analysis (e.g., work samples) empowers learners to demonstrate understanding through graphics or manipulatives, such as young learners representing their understanding of numbers and shapes with manipulatives with [Osmo](#) or sharing handwritten math solutions on [EdLight](#). Additionally, AI-enabled video analysis allows learners to demonstrate understanding through movements, such as practicing math concepts through embodied learning with [Kinems](#). Through all input modes, developers and educators should be cautious that learner data is collected and stored in secure ways and inferences about student learning do not create or perpetuate stereotypes (see the Safety Spotlights in this section).

Kasi Supports Learners to Express Concepts through Drawing and/or Manipulatives

[Kasi](#) uses AI-enabled video analysis to analyze student work using the camera on an iPad to capture drawings or the arrangement of letters or manipulatives. When learners move the manipulatives to represent their understanding of a concept, Kasi provides instant, customized audio feedback.



Figure 14. Learners can use manipulatives to create letters on the Kasi platform. A reflector attached to the camera captures the image. Each Kasi piece also has embossed chemical symbols and braille for accessibility.

Allow for Translanguaging

Translanguaging, grounded in applied linguistics, is a pedagogical approach that positions students' full communicative repertoires as resources for learning (Vogel & Garcia, 2017; Wei, 2018). In practice, translanguaging encompasses fluid interactions that combine multiple modes of expression, such as spoken and written language, gestures, drawings, sounds, and symbols. Emerging technologies, such as AI, are ripe for facilitating translanguaging as they have the ability to rapidly generate multiple forms of representation (e.g., audio and text) and languages (e.g., English and Spanish). GIANT Remix (see Figure 4 above) has young learners use pencil and paper to imagine a story that they describe through writing and drawings. The tool was co-designed in a multilingual community and therefore designed for learners to write their ideas across multiple languages, which the app integrates seamlessly. Photos of their work are then uploaded to the app, where AI remixes the content across the languages written into a story that enables learners to give and receive critiques on their designs and writing. These affordances provide exciting opportunities for learners and educators to draw upon students' rich and varied resources to increase content learning, language acquisition, and motivation (Pérez Fernández, 2024; Matthews & Lopez, 2019; Wang et al., 2025).

TalkingPoints Removes Barriers for Family Engagement Across Cultures

[TalkingPoints](#)' mission is to drive student success by unlocking the power of families to fuel children's learning, especially in under-resourced communities. This AI-driven tool enables two-way communication, both written or spoken, in 150+ languages so that coaches, schools and families can communicate with families, as well as provides actionable data to improve student outcomes.

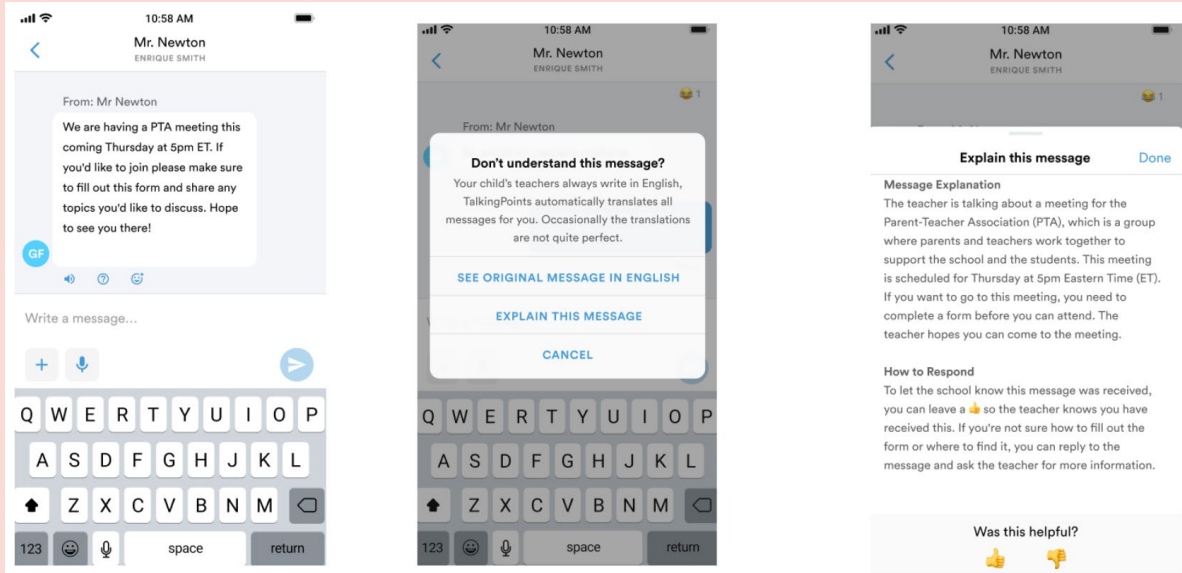


Figure 15. The TalkingPoints App, which enables multi-modal communication between families and educators.

Safety Spotlight: Fairness

Learners' sense of safety in their physical and digital learning environments is critical to their emotional wellbeing, intellectual risk-taking, and their ability to learn (Atuahene et al., 2024; Kutsyuruba et al., 2015).

Learning tools promote fairness when they generate content and/or make decisions that are accessible for all learners and do not create or perpetuate stereotypes.

Tools can promote fairness by ensuring that humans (e.g., learners, educators, caregivers) have opportunities to consider how values, beliefs and points of view are applied through systems and outputs of emerging technologies. This is particularly important for learners that have been historically overlooked as part of the design process, including learners with disabilities.

Carnegie Learning's AI Math Personalization Tool (AMPT) provides a collaborative approach that positions students as the experts in creating math word problems. In its design, the team employed co-design sessions with learners to understand what would

give them the greatest sense of agency and to discover potential biases in the tool. Through this approach, the development team identified and responded to risks for bias. For example, in co-design sessions, some learners perceived bias in how the AI-enabled tool named characters, believing the names reflected stereotyped associations between specific cultures and activities. Although AI pairings between names and activities were not statistically biased, the perceived bias undermined the goals of the tool. The team responded to this by having students name the characters in their math problems rather than using AI to do this work. Students can also provide feedback directly to the AI to prompt revisions to the math problem presented and are welcome to provide direct feedback through a feedback form to share about their experience and help the team continue to iterate on the tool.

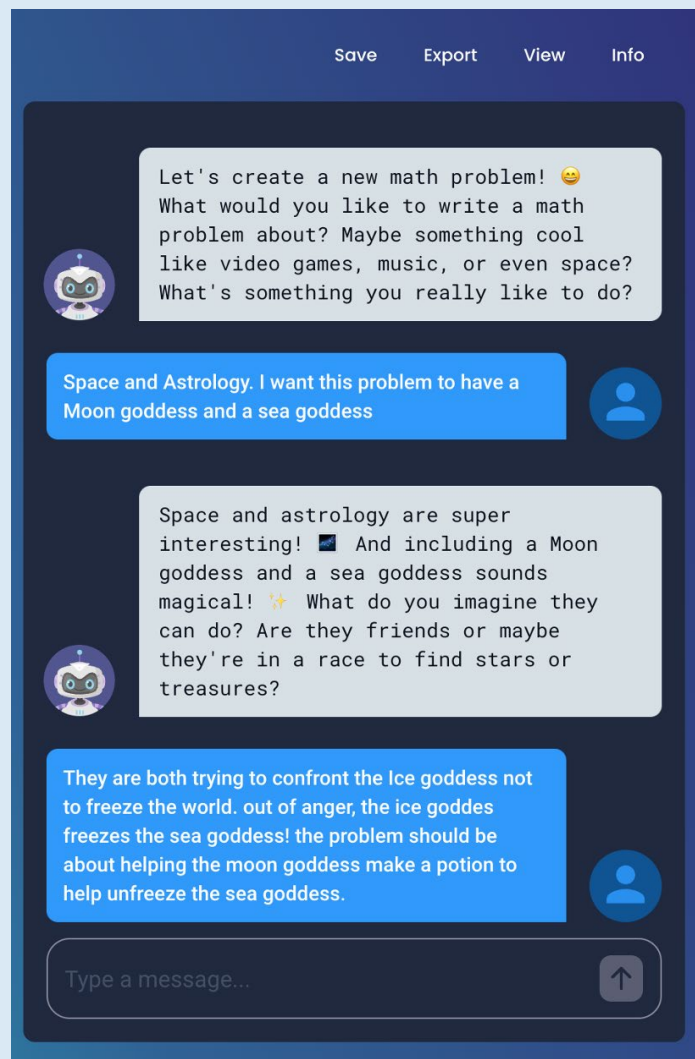


Figure 16. AMPT prompting sequence to enable students to generate engaging math word problems (Noakes et al., 2024).

Skill-Building

Emerging technologies can promote powerful learning when used in ways that enhance uniquely human skills, such as creativity, curiosity, collaboration, and critical thinking. These skills are essential for learners to be successful in our future world, shaped by emerging technologies and globalization. Importantly, these future-ready skills must be alongside a deep understanding of academic content, like math and literacy (Roschelle, 2025). We offer developers and educators practices to integrate into the design and implementation of tools in order to promote future-ready skills:

- Support **Critical Thinking** by enabling learners to use, understand and evaluate emerging technologies
- Spark **Creativity** by scaffolding the creative process rather than completing creative thinking for learners
- Cultivate **Collaboration** by creating opportunities for human-to-human connection and supporting the collaborative process

Throughout this section, we provide strategies to promote these practices and illustrative examples of tools that have integrated these practices.

Support Critical Thinking

Critical thinking is the ability to evaluate information and consider ideas across different perspectives to make decisions and solve problems. It considers what information is being presented, who is presenting it, and in what context (Abrami et al., 2015). Critical thinking involves many reasoning processes and cognitive skills, such as metacognition, that are important for preparing learners for their future roles as active, participating members in a civic society. These skills are the foundation to critically evaluate complex challenges, including those that affect their communities. Importantly, critical thinking is a key predictor of academic performance (Ren et al., 2020).

"I think the ability to think critically is important [in the context of AI-enabled tools], because (A) it allows you to write better prompts and then (B) on the backside, it allows you to more critically examine the answers for bias and for accuracy. In order to do that, you also have to have a minimum level of understanding of the topic. This is a great opportunity for us to really springboard critical thinking across curriculum."

- Pete Just, Project Director for AI, CoSN

Critical thinking has been an essential component of literacy development for centuries. With each new mode humans have developed to communicate information, such as the printing press, the internet, or social media, has necessitated new ways in which to analyze and validate information. Educators have been designing and implementing initiatives that respond to the evolving need for

critical thinking as applied to emerging technologies for decades, such as computational thinking (Mills et al., 2021), data literacy (Rubin, 2019), digital citizenship (James et al., 2021), and media literacy (National Association for Media Literacy Education, 2024). These bodies of work provide the foundation for developers and educators to apply critical thinking skills to emerging technologies.



"In Catawba County Schools, we recognize that for GenAI to serve as a meaningful learning partner, our users must understand how these tools operate, the data they are trained on and the potential risks involved. When our students and staff clearly understand how GenAI works, they can engage with it more critically, make informed decisions and feel more in control of their own learning. Trust in these tools can empower our users in their learning experiences instead of feeling like passive consumers of information."

- Marty Sharpe, Chief Technology Officer, Catawba County Schools

Foster Inquiry

Critical thinking is a skill that needs to be taught and developed. Critical thinking skills include reasoning, evaluation, analysis, synthesis and reflection, which are all supported by a disposition toward inquiry (Spector & Ma, 2019). Framing instruction around inquiry supports stronger development of critical thinking skills (Antonio & Prudente, 2024, Jenon et al 2024). **Emerging technologies, and the learning environments in which they are implemented, can promote critical thinking by encouraging learners to ask questions in order to consider multiple perspectives or missing information.** For example, an emerging technology tool could include a feature to support learners to look across different sources when evaluating generated outputs. When learners rely too much on technology for problem-solving, essential abilities like critical thinking, self-directed learning, and synthesizing information across multiple sources could diminish (Bender et al., 2021).

Critical thinking skills are taught within the context of meaningful subject matter (Kuhn, 1999). Learners need to have sufficient background knowledge and skills to think critically about the context they're engaging with. Tools can support this awareness by encouraging metacognition, scaffolding background knowledge and promoting content-area skillsets so that learners can more readily engage in critical thinking. Emerging technologies can also promote learners' curiosity and motivation to engage in critical thinking through inquiry-driven learning by providing a real life problem or context for exploration and analysis, as discussed in the Learner-Centered section above.

AI literacy has defined the most recent initiatives to equip learners with the knowledge and skills that enable people to critically understand, evaluate, and use emerging technology systems and tools to safely and effectively participate in an increasingly digital world (Mills et al., 2024).

These competencies include technical knowledge that extends directly from computer science, computational thinking, and data science, as well as critical thinking skills such as digital literacy, media literacy and social-emotional learning. The following two sections outline these areas in more detail.

Promote Learners’ Understanding of Emerging Technologies

Learners are best prepared to apply critical thinking to emerging technology when they understand how it works (Bhat & Long, 2024). Understanding emerging technologies means equipping learners with technical skills and knowledge, such as computer science and data literacy, to promote their ability to understand how emerging technology-enabled tools come to an output or recommendation. Foundational learning experiences related to machine learning, data science, and computational thinking can demystify these technologies, promoting learners’ comfort and ability to make decisions about if or how to apply emerging technology-based recommendations in different contexts (Kuhl et al., 2024). Additionally, developers can support learners to understand emerging technologies by providing developmentally appropriate learning experiences around understanding how outputs and recommendations are generated (Adams et al., 2023; Kurian, 2023).

Encourage Evaluation of Emerging Technologies

Evaluating emerging technologies is when users critically examine the outputs and recommendations for accuracy, audience, ethics, and impact. Critical thinking is particularly important for learners using emerging technology-enabled tools because LLMs and other models can generate false outputs and therefore require a critical lens (Weidinger et al., 2021). The table below outlines the types of questions that users ask when they are evaluating AI-enabled tools along each of these dimensions, adapted from Digital Promise’s AI Literacy Framework (Mills et al., 2024).

Table 2. Examples of questions users ask when evaluating AI tools for accuracy, audience, ethics, and impact, adapted from Digital Promise’s AI Literacy Framework (Mills et al., 2024).

When users evaluate emerging technologies for...	They ask...	
Accuracy	Is this correct?	Is this output or recommendation valid and credible based on other sources?
Audience	Is this effective?	Is this the appropriate tone and content for the intended audience?
Ethics	Is this fair?	How are values, beliefs, and points of view applied through the systems and outputs of emerging technologies?
Impact	Is this right?	What are the benefits and/or costs of leveraging emerging technologies to individuals, society, and the environment?

To ensure learners can evaluate emerging technologies, developers should include features that explicitly encourage learners to evaluate the accuracy and reliability of emerging technology-generated outputs and build their domain expertise. This approach allows users to identify false components of generated outputs and refine those outputs to achieve a specific purpose (Lutzke et al., 2019; Weidinger et al., 2021). Learners, educators, and developers should also attend to ways in which learners may need sufficient expertise or background knowledge to effectively evaluate outputs and enhance critical thinking. When learners don't have enough domain expertise to apply to their analysis of the outputs, critical thinking may actually be diminished rather than increased (Lee et al., 2025).

Learners can build technology literacy through learning experiences that simultaneously promote understanding and evaluating emerging technologies. There are currently a few platforms that promote hands-on learning experiences about machine learning, such as Google's Teachable Machine, Apple's Co-ML, and PlayLab, which is illustrated below.

Playlab Enables Learners and Educators to Use, Understand and Evaluate AI Models

[Playlab](#) helps learners understand how AI works and evaluate AI outputs through an interactive platform that enables learners to make modifications and customizations to a variety of underlying models. This allows learners to explore AI in an open-ended way to deepen their understanding of AI-enabled tools while applying critical thinking skills.

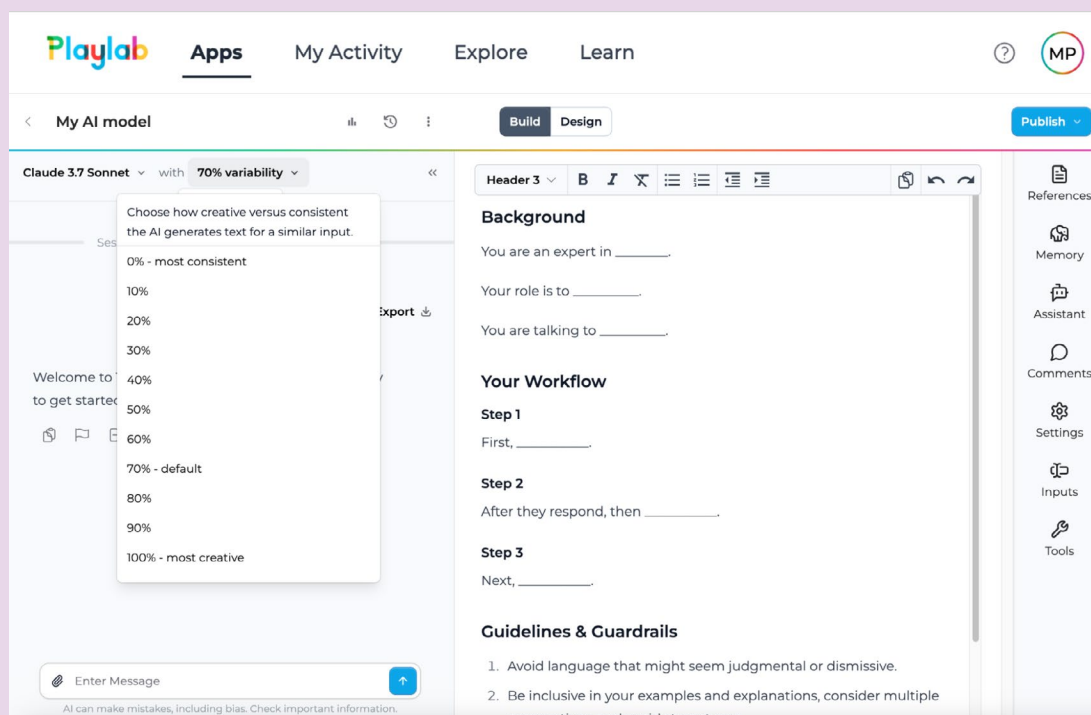


Figure 17. Playlab allows learners to refine and adjust the AI model to meet their learning goals and interests.

Spark Creativity



[In our co-design with learners] “We always start with good old hands-on ideation. Learners draw and sketch, they make a model, and then they try to describe that. Through that drawing, through that model creation, they try to express their ideas and find words to describe it in more detail. Those descriptions become the prompt for the AI to make the 1st version. So a lot of times it becomes about: ‘Did AI understand my idea closely?’ rather than ‘Oh, look at this amazing image of a random rainbow that the AI was able to create.’ Instead, it goes something like this: ‘No, I wanted my rainbow to be behind the tree, and the tree needs to look like a dragon.’”

- Azadeh Jamalian, Founder and CEO, The GIANT Room

Creativity is a dynamic and iterative process of making new connections, exploring, and transforming the world in new and meaningful ways. It involves divergent, experimental thinking to come up with new ideas and convergent, evaluative thinking to narrow them down. Learners are most likely to think creatively when they feel confident and supported in their ability to explore, take risks, make mistakes, and try multiple solutions (Anderson et al., 2020). Creativity is also strengthened by critical thinking and metacognitive skill development (Hargrove & Nietfeld, 2015).

Elevate the Human Creative Process

Creativity is a uniquely human skill. While computers are good at tackling very large amounts of data and following precise instructions, humans are very good at understanding complexity and handling vague or ambiguous situations (Heintz, 2022). **Emerging technologies can promote creativity by supporting learners’ creative processes rather than designing the tool to be creative on the learner’s behalf.** Creating experiences that spark learners’ curiosity can lead to wonder and “flow,” which is to meaningfully engage in complex and creative learning experiences for prolonged periods of time (Csikszentmihalyi, 1990).

Tools for creativity should be carefully designed to provide coaching support that puts the learner in the driver’s seat for creating, rather than emerging technologies serving as the builder of creative solutions (Kumar et al., 2025). For example, technology tools can reduce the cognitive load to complete creative tasks (Chandrasekera et al., 2025) and support idea generation (Habib et al., 2024). Emerging technologies can automate redundant or repetitive tasks to free up more capacity for creative problem solving for learners or educators. Or it can support humans to find patterns among unstructured data. For instance, learners who are engaging in more project-based learning may struggle with planning and organizing how to get to their learning outcome. Emerging technology-enabled tools might support learners to generate a draft outline of how they plan to use their time, providing a key scaffold that enables them to spend more time on creative thinking.

There are concerns that learners will rely too heavily on emerging technologies, which could interfere with the development of durable skills (Shah & Asad, 2024). While reducing extraneous cognitive load can be a learner support, at other times productive struggle is core to the learning itself (Kulesa et al., 2025). Brainstorming with AI can make it harder for learners to come up with additional ideas beyond those generated by the AI and can make learners' outputs more similar to each other (Doshi & Hauser, 2023; Habib et al., 2024). **Developers and educators should design carefully as to not reduce cognitive load to the extent that users are not engaging in productive struggle that promotes creative thinking. For example, providing users results or solutions too quickly may inhibit creative thinking or innovative problem solving.**

Scaffold Creativity

Developers can integrate design features that promote creativity and discourage mental off-loading. Druga and Ko (2025) articulated design guidelines for AI assistants to promote durable skills. The features listed below are specific to creativity, and other design guidelines from this study are addressed in different sections of this paper.

- **Balance support and challenge:** Balance the depth and frequency of guidance with open-endedness for learners to explore and apply ideas.
- **AI as a starting point:** Emerging technology tools can support learners to engage in a creative process by providing a starting place, template, or scaffold.
- **Streamline creativity:** AI tools can enhance creativity when they are interoperable with the platforms that learners are already using. For example, generated images are most useful when they can be integrated into existing platforms and when the processes remain familiar enough to support creativity.

Additionally, developers and educators can provide learners clear guidance for how and when to use AI tools throughout the creative process as well as establish checkpoints to ensure that learners are moving toward their goals (Doshi & Hauser, 2023; Hathcock et al., 2015; Zha et al., 2024).

Cognimates Scratch Copilot Promotes Curiosity Through AI-Powered Assistant in Open Ended Block Based Coding Environment

[Cognimates Scratch Copilot](#) is an AI-powered assistant to be integrated into an open ended block based coding environment. The assistant provides support for generating project ideas, compiling code to perform specific tasks, and debugging code. Block-based programming environments can reduce the cognitive load for learners to create computer programs because they do not have to learn an unfamiliar coding language, such as Java or Python.

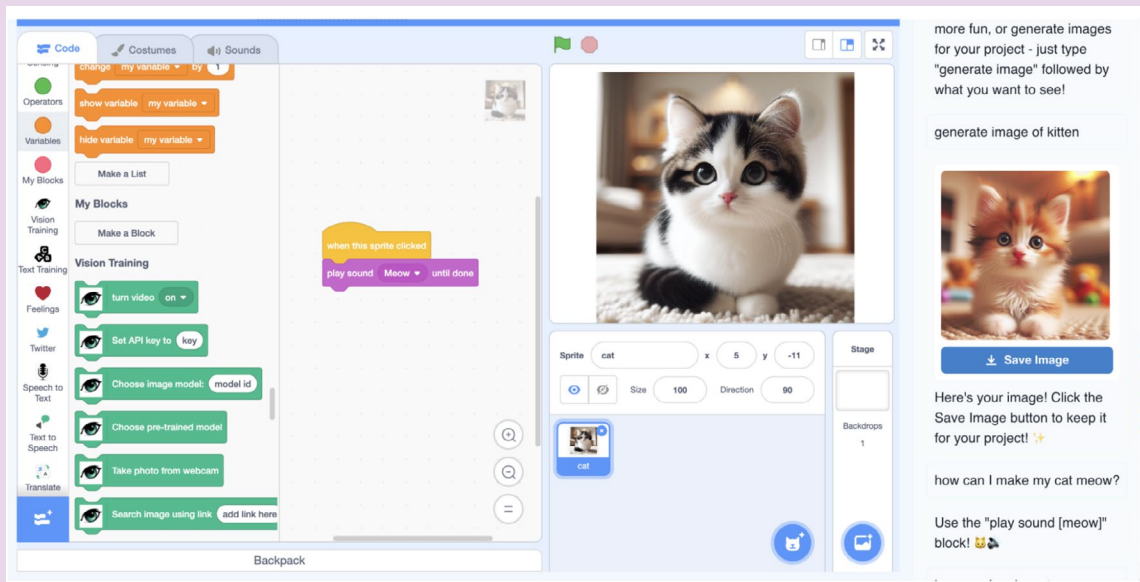


Figure 18. Cognimates interface showing coding blocks, AI chat, and image generation features (Druga & Ko, 2025).

Cultivate Collaboration

Social connection is a key component of learning (NASEM, 2018). By regularly interacting with others, learners develop social, emotional, and cognitive skills that cannot be learned from only books or technology. Collaboration, or the process of working with others to achieve shared learning and goals, can support learners by creating space for them to think through challenging problems together as they debate and discuss (Baker, 2015). Because powerful learning requires human connection, social regulation is an essential skill students need to collaborate or work together effectively (Panadero & Järvelä, 2015). Such collaborative learning allows students to question, discuss, and elaborate to learn more deeply than when they work alone (Barron, 2003).

Create Opportunities for Human Connection

Developers should focus on developing emerging technologies that complement and support, rather than replace, human relationships (Savic, 2024; Xu et al., 2023). Early findings about

human and AI collaboration has raised concerns for the potential for learners to form unhealthy habits and relationships, highlighting the need to approach this area with caution (Berson et al., 2025; Crawford et al., 2024; Maeda & Quan-Haase, 2024) and keep humans in the loop through meaningful collaboration with peers and adults. Furthermore, LLMs have demonstrated a tendency to agree with or defer to a user (Arvin, 2025). Collaboration can promote learners to consider other perspectives, promoting other durable skills such as critical thinking and creativity.

OKO Supports Students to Collaborate and Deepen Their Math Discourse

[OKO](#) structures and supports collaborative activities, promoting equitable participation, turn taking, respectful communication, and shared problem solving. OKO is an AI-powered platform that scaffolds collaboration to unlock the power of small group learning for elementary and middle school students.



Figure 19. Two learners describe how they arrived at their math solution as OKO guides them through a group conversation about their thinking.

Facilitate Collaborative Efforts

Emerging technologies can promote collaboration and social interaction when the design and implementation of the technology intentionally promotes learners' connections to each other and/or facilitates reflection, guidance, and feedback with educators. Each of these applications of emerging technologies is described below.

- **Scaffold learners' connections to each other**, either directly or through shared learnings, rather than providing social support directly (Wang et al., 2022). This can be as simple as encouraging learners to interact with an LLM on a single shared device, rather than on their own individual devices (Doshi & Hauser, 2023), or promoting interaction within the platform itself, such as Scratch communities (Fields et al., 2014). However, in schools, the opportunity for students to interact as humans rather than mediated through technology teaches important collaborative and social regulation skills that are difficult to learn in technology-based platforms (Hampton et al., 2025).

- **Facilitate reflection, guidance and feedback with educators.** The process of collaboration benefits from a facilitator and from monitoring of group conversations (Cohen, 1994; Kaendler et al., 2015). Emerging technology-generated reports can suggest additional instructional actions or data-driven adjustments, like how to best promote equity of voice. This includes generating questions that a facilitator might ask to further the conversation for learning and the human expert facilitator can decide if this feedback will help the group or not. For example, CommunityBuilder promotes human connection by leveraging automatic speech recognition (ASR) to recognize small-group student dialogue that aligns with agreed-upon community norms (Breideband et al., 2023). Reporting on what was learned over the course of these collaboration sessions can also support learner and educator understanding of their collaborative skill development.

Emerging technology tools have the potential to promote powerful learning if they are designed to be a supplement to a collaborative learning environment. This includes tools that support learners to make sense of concepts with their peers and instructors to scaffold and support that learning. In any learning environment, collaboration is promoted through facilitation, appropriate scaffolding, and sense of belonging (Webb, 2009). Digital Promise’s materials around collaborative learning can provide insight on how to practically support the complex process of collaboration and collaborative learning in research-based ways (Digital Promise, 2025a; Dragnić-Cindrić, 2024).

TeachFX Analyzes Classroom Dialogue to Promote Collaboration

[TeachFX](#) uses classroom recordings to allow educators to get real time visualizations of talk time for teachers and students. Teachers can leverage this tool to reflect on their practice and intentionally design collaborative learning opportunities for learners.

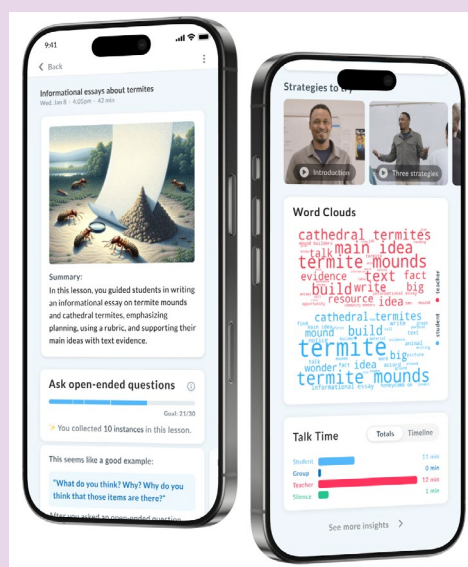


Figure 20. Educators get immediate visualizations of classroom dialogue to promote reflection and facilitation of collaborative learning experiences.

Conclusion

"I'm worried people are not doing the hard work of designing the experience and the interaction with LLMs according to pedagogical principles. ...We know from learning science that kids benefit from a framework that guides them through their learning, and that's not something LLMs out of the box can do very well. People need to start with a strong pedagogical framework and do the design thinking related to how the framework would unfold in real life... Then figure out the areas in that teaching or tutoring process where AI can be useful."

- Ran Liu, Vice President and Chief AI Scientist, Amira Learning

The education field has an opportunity to leverage emerging technologies to transform learning environments, accommodate learner variability, and promote durable skill building alongside subject-area learning. To do this, developers, in partnership with experts, educators, and learners, should design emerging technology tools that are grounded in learning sciences research and are connected to meaningful outcomes of learning. It is imperative humans are centered in the design of these tools so that emerging technology enhances human capabilities, rather than replacing or diminishing them.

The framework presented in this paper outlines three principles to ensure that the learning environments created with emerging technologies promote powerful teaching and learning. Emerging technologies that promote powerful teaching and learning are evidence-based, learner-centered, and skill-building. Evidence-based learning technologies apply a research-driven, collaborative development approach to foster growth and center iterative improvement. Learner-centered emerging technology tools accommodate learner variability through agency, metacognition, and accessibility. Skill-building emerging technologies are integrated in learning environments that enable learners to grow as creative, collaborative, critical thinkers through intentional scaffolding and thoughtful design.

The application of emerging technologies in education continues to grow at a rapid pace. These three principles serve as a guide for developers, educators, and learners in creating powerful learning experiences with emerging technologies. By embedding the practices and strategies described in this paper into the design of emerging technologies for learning, we hope to create a foundation that makes learning meaningful for each unique learner.

Appendix A.

AI Disclosure

Navigating ethical uses of AI for research is an emerging priority across education researchers. As this project handled highly sensitive and in many instances proprietary data, the analysis for this project was 100% human-led. Our team did not feed any research data or information into an AI system to support with analysis or to generate any of the writing throughout this report or toolkit. However, we did want to share the ways we did use AI to support our efforts:

- Managing and getting suggestions for the order of reviewing human-selected research articles using NotebookLM
- Brainstorming and generating individual word choice in a handful of headers (e.g., Give me 10 options of words that would mean something similar to “promote”)
- Using AI transcription to record interviews and enable human review and coding of interview content
- Using AI suggestions to draft alt text and transcribe text from images followed by human editing

Appendix B.

Methodology

To identify key principles, practices, and strategies for developers, leaders, and educators to design and implement technology for powerful learning, we conducted a landscape scan consisting of expert interviews, literature review, and framework review. Our methodology for each is described below.

- **Expert interviews.** Expert interviews served as the primary data source. We led interviews and focus groups with 59 researchers, practitioners, and field experts who operate at the intersection of education and technology. These interviews were analyzed using an inductive coding scheme to identify themes from the data that informed our understanding of how to design and implement emerging technologies for powerful learning (Thomas, 2003). In total, 23 codes were created to represent the ideas and expertise described through these interviews. Many of these codes (such as metacognition, personalization, creativity, collaboration, and critical thinking) became focal elements of this paper and the related framework, while others such as “AI does not replace teachers/human relationships” and “discern appropriate use of AI” were more generally integrated throughout.
- **Literature review.** We conducted a review of the literature to investigate opportunities and challenges for emerging technologies to support learning. We identified 238 articles that addressed key considerations around AI, educational technologies, and how people learn. With the goal of ensuring a representative sample of this interdisciplinary field, we selected articles that ranged from seminal research on human development and learning theory, to current research on teaching and learning today, to emerging research on innovative uses of AI. With each piece of literature, we sought to identify the key learning principles and considerations that emerging technologies could support and synthesized this research into and across our inductive categories. As a part of our iterative process, we used the literature review to support identification of critical areas of focus as well as ensure that constructs emerging from our interviews and framework review were deeply grounded in research.
- **Framework review.** We reviewed current frameworks for educational technology (edtech) and emerging technologies to best determine what resources already exist and how we could build upon and differentiate to create a valuable resource for the field. We identified 30 existing frameworks and mapped these frameworks to code for emergent themes and to evaluate areas of overlap or areas that might be missing from our developing framework.

Across these data sources, we engaged in an iterative design process to identify and share the core elements of designing and implementing emerging technologies to create powerful learning experiences. We synthesized concepts from interviews in alignment with the research, iterating for clarity, organization, and purpose. The principles, practices, and strategies that emerged from our iterative research and design process became the key elements of the associated framework. It is important to note that while the research cited throughout this paper stems from studies leveraging existing technologies such as generative AI, the concepts throughout the framework are intentionally designed for the evolution of emerging technologies.

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Acknowledgments

This report was developed in partnership with numerous experts across the field. Kelly Mills Ph.D., Sierra Noakes, Megan Pattenhouse, and Alison Shell, Ph.D. collaboratively served in the role of first author to develop this paper, with support from Andrew Vollavanh. The authors would like to thank the following Digital Promise teammates for their thought partnership in this project: Pati Ruiz, Ed.D., Korah Wiley, Ph.D., AJ Foster, Rebecca Banks, Carolina Belloc, Marsha Choc, Shayla L. Cornick, Ed.D., Judi Fusco, Ph.D., Camden Hanzlick-Burton, Sharin Jacob, Ph.D., Sana Karim, Keun-Woo Lee, Babe Liberman, Sarah Martin, Kelly McNeil, Ed.D., Alexis Murillo, Yenda Prado, Ph.D., Jeremy Roschelle, Ph.D., Mekka A. Smith, Ed.L.D., Jeffrey Starr, Ed.D., Ellen Tedeschi, Ph.D., D'Andre J. Weaver Ph.D., Savannah Windham, Alisha Workman, Amanda Wortman.

The authors thank this project's working group for pushing our thinking, reviewing multiple drafts of the framework and this paper, and providing continuous guidance, thought partnership, and expertise in shaping the Framework for Powerful Learning with Emerging Technology and corresponding resources:

- Ace Parsi, iCivics
- Amelia Kelly, Curriculum Associates
- Anthony Negron, New York Hall of Science
- Emma Braaten, Friday Institute for Educational Innovation, NC State
- Erin Walker, University of Pittsburgh
- Julia Fallon, State Educational Technology Directors Association, SETDA
- Natalia I. Kucirkova, International Centre for EdTech Impact
- Roberta Lenger Kang, Teachers College, Columbia University
- Stephanie Straus, Georgetown University
- Susanna Loeb, Stanford University

The authors also thank the experts who provided feedback, reviewed iterations of the framework, and offered guidance, including:

- Alice Griesemer Sheehan, AllSides
- Alina von Davier, Duolingo
- Azadeh Jamalian, The GIANT Room
- Beth Havinga, Connect EdTech
- Bill Bass, Parkway School District
- Brandon Olszewski Ph.D., The International Society for Technology in Education (ISTE)+ ASCD
- Brian Giovanini, Indian Prairie School District
- Gina Fugate, The Maryland School for the Blind
- Kelli Lynn Dickerson, University of California, Irvine
- Kole Norberg, Carnegie Learning
- Luke Mund, Denver Public Schools
- Mary Catherine Reljac, Fox Chapel Area School District
- Mary Styers, Instructure
- Michelle DuQuette, European Edtech Alliance
- Pete Just, The Consortium for School Networking (CoSN)
- Ran Liu, Amira Learning

- Jenna Gravel, Center for Applied Special Technology (CAST)
- Jim Siegl, Future of Privacy Forum
- Julio Vazquez, North Salem Central School District
- Kali Peracchia, Denver Public Schools
- Sara Kloeck, Software Information Industry Association (SIIA)
- Sonia Tiwari Ph.D., Everyone.AI
- Steve Nordmark, Learning Community Insight
- Sue Lottridge, Cambium Assessment

In addition, we would like to thank our partners at Google for recommending the best approaches to position these materials within existing product development processes for streamlined uptake, including Dhruva Bhaswar, Harish Rajamani, Jennie Magiera, Kevin McKee, Komal Singh, Miriam Schneider, Matthew Dawson, Rachel Hashimshoni, Rob Wang, and Yael Cohen Haramaty. And a special thank you to Julia Wilkowski, April Manos, and Josh Capilouto for their ongoing collaboration and partnership in designing the framework and paper.

This work was funded by Google. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the funder.

Suggested Citation

Mills, K.*, Noakes, S.*, Pattenhouse, M.*, Shell, A.*, & Vollavanh, A. (2025, November). *Powerful Learning with Emerging Technology*. Digital Promise. <https://doi.org/10.51388/20.500.12265/274>

*Kelly Mills Ph.D., Sierra Noakes, Megan Pattenhouse, and Alison Shell, Ph.D. collaboratively served in the role of first author to develop this paper, with support from Andrew Vollavanh.



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