LEARNING BRIEF

How is AI Being Deployed to Support Foundational Learning in Low- and Middle-Income Countries?

AI Observatory

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About the AI Observatory

EdTech Hub's AI Observatory and Action Lab exists to help drive greater equity in learning outcomes in the age of AI. The AI Observatory scans global trends, uses a hypothesis-driven approach to test practical applications, leads innovative pilots, and distils practical insights to support decision-makers in low- and middle-income countries.

Our goal is to ensure AI is integrated effectively and equitably, improving education systems and learning outcomes for all. EdTech Hub's AI Observatory is made possible with the support of the UK's Foreign, Commonwealth and Development Office.
https://edtechhub.org/ai-observatory/

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Abbreviations and acronyms

AfL	Assessment for Learning
DPL	Digital personalised learning
EGRA	Early Grade Reading Assessment
FLN	Foundational literacy and numeracy
GenAI	Generative AI
GRR	Gradual Release of Responsibility
IPA	Innovations for Poverty in Action
HIL	Human-in-the-Loop
LLM	Large Language Model
LMIC	Low- and middle-income countries
NIETE	National Institute for Excellence in Teacher Education (Pakistan)
PAL	Personalised adaptive learning
RCP	Read, Count, and Play
RCT	Randomised controlled trial
SDG	Sustainable Development Goal
TaRL	Teaching at the Right Level
TPD	Teacher Professional Development

Why this matters

Foundational literacy and numeracy (FLN) are the essential building blocks of lifelong learning, yet millions of children in low- and middle-income countries (LMICs) are being left behind. In 2022, the World Bank estimated that approximately 70% of 10-year-olds in LMICs could not read and understand a simple text, a condition it defines as *learning poverty*—and this crisis worsened considerably following Covid-19 school closures (↑World Bank, 2022). Without urgent action, an entire generation risks failing to acquire the basic skills needed for future learning and participation in the workforce.

Further evidence suggests that the crisis is not evenly distributed: children from the most vulnerable groups—including those in LMICs—are disproportionately affected. School closures during the Covid-19 pandemic compounded pre-existing inequities, with many children lacking access to remote learning due to digital divides and weak infrastructure (↑Science of Teaching, 2022). A study by ↑Patrinos et al. (2022) estimates that an 'average child' in an 'average country' lost approximately half a year of learning, though the magnitude of loss varies widely across contexts.

At the same time, there is global consensus that strengthening FLN requires solutions grounded in *what works*. Evidence shows that approaches such as structured pedagogy, assessment-informed instruction, and targeted teacher support can dramatically improve early learning outcomes.

> *"New education technologies are only as powerful as the communities that guide their use. Opening a new browser tab is easy; creating the conditions for good learning is hard."*
>
> ↑Justin Reich, 2025

UNESCO's guidelines emphasise that any innovation—including AI—must be designed in alignment with proven practices and contextualised for local needs and realities, or else it risks reinforcing existing gaps rather than closing them (↑UNESCO, 2021).

Through their work on the Science of Teaching platform,[1] RTI and the Gates Foundation have identified a list of topic areas that have been proven to effectively support foundational learning in low-resource or LMIC contexts. Focusing on the topic areas that cater to the delivery of FLN instructions in the classroom, and reframing them as *proven practices* (listed below) that support foundational learning, we aim to leverage the work done on the synthesis of evidence that identifies these proven practices, and provide AI-enabled use cases and examples that support them. Our analysis includes the limitations of the use cases, the opportunities that arise in mitigating them, and the strength of the evidence supporting them.

Proven practices supporting foundational literacy and numeracy (FLN)

- Assessment-informed Instruction
- Structured pedagogy
- Remediation
- Language of instruction
- Materials development
- Teacher professional development

[1] https://scienceofteaching.site/. Retrieved 1 December 2025

What we’re learning

Building on the work of the Gates Foundation and RTI International, which captures proven practices for improving FLN outcomes, we consider how AI can accelerate these practices by providing examples and addressing their limitations and opportunities. Existing evidence suggests that effective implementation sees these practices complementing each other, and that large and scalable gains in FLN are usually achieved through packaged complementary approaches that typically bundle these practices into structured pedagogy and teaching at the right level (TaRL) approaches (↑Asghar & Dintilhac, 2025).

The list of use cases and AI products considered for each proven practice in the Science of Teaching framework is not exhaustive. While there are many more use cases and products listed in the AI-for-education.org repository,[2] our focus has been on products that have some form of evidence of their efficacy and impact, or that attempt to leverage the aforementioned established and proven practices in education. Considering the nascent stage of the application of AI for education, the evidence for the studied examples is largely self-reported or provided by qualitative analyses, with robust long-term studies still rare or currently underway, and results still to be published.

Assessment-informed instruction

The utilisation of Artificial Intelligence (AI) for assessment-informed instruction represents a significant shift in educational practice, moving from intuition-based teaching towards evidence-informed pedagogy. According to ↑Science of Teaching (2023, p. 2), assessment-informed instruction “refers to the activities undertaken by teachers—and sometimes students, head teachers, and coaches—that provide timely information to track progress and modify subsequent teaching and learning activities”. The most important component of assessment-informed instruction, and perhaps the most challenging, is supporting teachers in taking specific actions in response to the information generated through assessment. Assessment for learning (AfL), part of proven classroom practice in assessment-informed instruction, focuses on ongoing, often informal, evaluation of the teaching and learning

[2] https://ai-for-education.org/ai-products/. Retrieved on 1st December 2025

processes in a classroom to guide adaptations to instruction and target remediation and enrichment (↑Science of Teaching, 2022).

AfL is most effective when what is being taught and assessed aligns with students' abilities, needs, and learning goals (↑Hwa et al., 2020).

For the effective implementation of AfL in LMICs, teachers come head-to-head with the challenges of determining what to assess, finding time for assessment and remediation, recording and tracking results, and using those results to inform instruction (↑Science of Teaching, 2023). The emerging use of teacher-facing AI tools for assessment-informed instruction addresses these challenges by automating quick checks, capturing results, grouping students, organising data, and generating simple instructional feedback. (↑Asghar & Dintilhac, 2025). It appears AI's most important contribution to assessment-informed instruction is its ability to support routine classroom practices required for assessment-informed instruction, which contribute to established approaches such as structured pedagogy and TaRL.

Examples and evidence

AI tools for assessment-informed instruction with an offline-first design protect equity and resilience, ensuring that even schools with limited connectivity can use core functions such as assessment, student grouping, and instructional feedback, all of which support assessment-informed instruction. At the same time, schools with better resources and connectivity can access updated content and enhanced analytics (↑Asghar & Dintilhac, 2025).

The **Nyansapo AI** App has demonstrated effective use of AI to support assessment-informed instruction. The 2025 *Read, Count and Play* RCP pilot endline study in Kitui County, Kenya, provides strong evidence that structured, TaRL-aligned learning camps supported by AI-powered, offline-first assessments can drive measurable gains in foundational literacy. Implemented across ten schools with 859 learners, the intervention improved overall literacy from 36% at baseline to 54% at endline, an 18-percentage-point increase, with eight of the ten schools showing substantial progress and gains as high as +64% (↑Nyansapo AI, 2025). The evidence suggests that short, intensive, group-based literacy interventions, when supported by simple, AI-driven digital tools and continuous coaching, can produce meaningful improvements even in rural, low-connectivity environments.

Automating routine assessment tasks while keeping the teacher in the loop strengthens teacher agency and instructional decision-making (↑Asghar & Dintilhac, 2025).

In the Philippines **CoBRA pilot**, students completed a self-administered AI-powered reading assessment (oral reading fluency, listening, and silent comprehension) in an average of 4–8 minutes, with immediate results and subsequent automatic grouping of students, aligned with the Philippines Informal Reading Inventory (Phil-IRI) standards. Early feedback, with 90% of teachers indicating that having timely, curriculum-aligned evidence made it easier to target instruction and adjust support for learners, suggests a pathway to improved instructional quality while keeping teachers at the centre of decision-making (↑RTI International, 2022).

AI tools must prioritise the least-connected learners through offline-capable, low-cost, language-aligned design (↑Asghar & Dintilhac, 2025). This principle is reflected in the deployment of Wadhwani AI's Vachan Samiksha[3] in the Indian states of Gujarat and Rajasthan, which has enabled 3.3 million assessments across 50,000 schools and 230,000 teachers. While evidence of learning gains is limited, teachers report improved accuracy and a shift from infrequent manual checks to regular small-group diagnostics.

Limitations

Despite its promise, AI-enabled assessment-informed instruction faces notable limitations. Automated scoring for expressive tasks, such as oral reading, remains inconsistent, risking learner misclassification and weakening approaches such as TaRL and remediation. These accuracy challenges are especially pronounced for multilingual learners and mid-range performers, underscoring the continued need for strong human review to ensure fairness and instructional alignment (↑RTI International, 2022).

Another common limitation is the gap between AI-generated results and actionable instructional guidance, which is essential for TaRL/remediation

[3] https://www.wadhwaniai.org/impact/education/oral-reading-fluency/. Retrieved 1st December 2025

and structured pedagogy routines. While many AI tools rapidly produce scores, they often fail to translate those scores into clear grouping rules, targeted task selection, or next-step teaching strategies aligned with national curricula. Without this instructional bridge, AI risks speeding up assessment without improving the quality of differentiated instruction.

Low digital literacy and insufficient teacher preparation directly affect the consistent use of AfL, TaRL, and remediation routines. Teachers require structured training and ongoing support to interpret AI insights, adjust grouping, and deliver targeted instruction. Without this scaffolding, digital tools may create confusion or mistrust rather than enhancing teacher agency, limiting their effectiveness in strengthening classroom instruction (↑Holmes & Miao, 2023).

Summary of evidence

Evidence for AI-enabled assessment-informed instruction is promising but still emerging, as most examples come from short-term pilots, programme reports, and early implementation studies. The findings indicate that AI tools can reinforce proven practices such as AfL, TaRL, and structured pedagogy, resulting in improved diagnostic efficiency, expanded assessment coverage, and more consistent use of formative evidence. However, evidence on the reliability of automated scoring across diverse languages and learner profiles, and on how effectively teachers integrate AI-generated insights into differentiated instruction, remains limited.

Remediation

In classrooms across LMICs, students are often several grade levels behind in foundational skills. Given this mismatch between where children are and where they need to be, remediation is essential and must be implemented at scale before learning gaps expand and permanently reduce children's human capital development in the system.

Remediation, as defined in the ↑Science of Teaching (2022) report, involves identifying specific learning gaps and providing instruction precisely at the learner's current level of understanding. This approach aligns with TaRL methodology, which adapts instruction to learners' proficiency rather than to grade level (↑Davidson et al., 2022; ↑Muralidharan et al., 2019).

Across LMICs, remediation approaches such as TaRL programmes, personalised adaptive learning (PAL) programmes (which use technology to target individual skills for specific children), and tutoring-based interventions have shown strong potential to close learning gaps when implemented with fidelity and regular feedback cycles (↑Science of Teaching, 2022). These results form the foundation on which emerging AI-enabled remediation efforts now build.

By leveraging adaptive learning algorithms, natural language processing (NLP), and Automatic Speech Recognition, AI can support teachers in targeting instruction to each learner's needs, facilitating mastery-based progression (↑AI For Education, 2023; ↑Alkhasawneh, 2025; ↑Muralidharan et al., 2019)

Examples and evidence

Emerging AI tools are evolving, and combining elements of the three established remediation models—TaRL, PAL, and tutoring interventions. Hybrid AI workflows blend digital personalised learning (DPL) with human-led remediation, reinforcing remediation and TaRL core processes, as they operate as lightweight 'co-pilots' that help teachers and community tutors carry out proven routines more efficiently, while ensuring contextual fit in schools with limited time, infrastructure, or connectivity.

Edulution[4] in South Africa illustrates this emerging hybrid model. The programme blends a DPL platform with structured small-group tutoring delivered by community youth coaches, while teachers use digital assessment insights to adjust classroom instruction. Early programme data shows promising improvements: 28% of all participating learners achieved grade level by year-end, rising to 36% in schools engaged since January 2024, compared with 32% in 2023 and only 3% at programme inception in 2021. These gains suggest potential for combining personalised digital practice with human-led tutoring for grouped remediation (↑Edulution, 2024).

Countingwell[5] in India offers a similar AI-assisted variation, functioning as a diagnostic and decision-support tool for teachers. By highlighting misconceptions, identifying students needing help, and recommending follow-up tasks, it supports more structured, data-informed remediation. Countingwell's 2022 *State of Maths Learning Report* shows that poor

[4] https://www.edulution.org/south-africa-programme. Retrieved 1st December 2025.

[5] https://countingwell.com/school.html. Retrieved 1st December 2025

word-problem comprehension is a major driver of low maths scores, with only 1 in 4 students able to solve such problems unaided. The report also finds that one in four learners lacks basic calculation skills from earlier grades before intervention and that Countingwell's adaptive diagnostic algorithm, which targets and remediates prior-grade learning gaps, more than doubled the percentage of students proficient in applying language-based problem-solving skills, increasing from 28% to 60%, demonstrating early potential for AI-supported remediation (↑Shah, 2022).

Limitations

While AI shows strong potential for remediation, key challenges remain. A key limitation for integrating AI into TaRL-style remediation is the time burden required for effective remediation cycles. Evidence from large-scale TaRL implementations (e.g., Zambia) shows that schools struggle to consistently allocate dedicated time for daily or term-long catch-up sessions. Even when AI makes assessment and grouping faster, these structural time constraints persist, limiting the extent to which teachers can act on AI-generated insights (↑IPA, 2022).

Another limitation is the shortage of qualified mentors or instructional coaches trained in remedial pedagogy. TaRL and tutoring models rely heavily on continuous supervision and support, yet many AI-enabled remediation tools provide insights without the human coaching needed to help teachers interpret data and adapt instruction. In low-digital-literacy environments, this gap can leave teachers overwhelmed or unsure how to translate AI recommendations into high-quality remediation (↑IPA, 2022).

AI does not automatically resolve classroom implementation challenges, such as large class sizes, multi-grade groupings, and limited space for differentiated instruction. These contextual constraints can weaken the fidelity of remediation routines, even when AI accurately identifies learner needs (↑Cunha et al., 2022; ↑Urfah et al., 2024). Without supportive school structures, AI-enabled remediation risks becoming an assessment tool rather than a fully effective instructional intervention.

Summary of evidence

Evidence for AI-enabled remediation in LMICs is promising but limited, with most findings drawn from small pilots, implementer reports, and hybrid programme evaluations rather than large-scale or long-term randomised controlled trials (RCTs). Beyond the Nyansapo AI RCP pilot, which demonstrated meaningful literacy gains in a structured, TaRL-aligned setting, tools such as Edulution and Countingwell report progress mainly through programme-generated data. These emerging cases indicate a clear trend: EdTech or AI systems originally designed for DPL or PAL are evolving to incorporate remediation practices, such as grouping, targeted support, and teacher-centred guidance, aligning more closely with proven models such as TaRL, tutoring, and structured pedagogy.

Early evidence suggests that such multimodal tools can help teachers tailor instruction, support catch-up classes and camps, and strengthen early diagnosis in foundational literacy and numeracy, while offering flexibility for LMIC contexts, including curriculum alignment, offline-first design, and varied digital literacy among teachers. Yet the evidence base remains weak, with limited causal attribution, uncertain long-term impacts, and variable fidelity to remediation routines as tools scale.

Structured pedagogy

The scale of unfinished learning demands urgent investment in instructional reforms like structured pedagogy, supported by strong teacher guidance and consistent implementation. At its most basic, structured pedagogy is a coordinated, integrated approach that includes teacher lesson plans, student materials, training, and ongoing support, all delivered through a planned, structured approach. Successful structured pedagogy relies on the system to ensure coordination among relevant actors (↑Benjamin & Dubeck, 2022).

Building on these foundations, AI is emerging as a pivotal enabler of structured pedagogy in LMICs. AI-driven platforms can support teachers by designing adaptive lesson plans, personalising learning pathways, and providing real-time instructional feedback. This has the potential to strengthen pedagogical consistency, improve content relevance, and accelerate curriculum alignment (↑Dennison et al., 2025).

AI can strengthen the implementation of structured pedagogy by helping teachers align its core components—lesson planning, instructional sequencing, materials development, and ongoing professional support in a coherent, curriculum-driven manner. By automating aspects of lesson preparation and providing step-by-step guidance based on established pedagogical models, AI reduces the cognitive and administrative burden on teachers while enabling more consistent use of evidence-based teaching practices (↑Aslam et al., 2025).

Examples and evidence

The **EIDU** platform in Kenya integrates DPL and the *Tayari* structured pedagogy programme, creating a model aligned with classroom practice rather than serving as a supplementary tool. EIDU's mobile application is deployed on low-cost Android devices in pre-primary classrooms in Kenya and uses personalisation algorithms to tailor learning to individual learners' needs. Aligned with Kenya's pre-primary competency-based curriculum, the EIDU platform provides high-quality content, including *onecourse*,[6] and assists teachers by offering digitised *Tayari* structured pedagogy resources. This integration ensures that learners benefit from DPL content that reflects the teaching they receive in the classroom, while it is also being personalised to their individual progress, a significant step in the structured pedagogy approach. Preliminary analysis from an RCT evaluating the DPL-structured pedagogy model in Kenyan pre-primary learners (aged 4–5) indicated a significant overall effect size of .425 SD in improving learning outcomes (↑Daltry et al., 2023).

Similarly, as structured pedagogy requires coherent instructional flows and ongoing professional development for teachers, AI can support these processes by generating materials that guide educators through sequenced instructional steps (↑UNESCO, 2021). The **NIETE** platform, deployed in schools in Islamabad, Pakistan, illustrates this potential: centrally produced AI-generated lesson plans based on frameworks such as Concrete Pictorial Abstract, Inquiry-Based Learning, and Gradual Release of Responsibility (GRR) have helped standardise instructional practice, improve classroom participation, and promote inquiry-led learning across schools. The accompanying teacher training modules and frequent coaching play complementary roles in delivering structured pedagogy through this programme (↑Aslam et al., 2025).

Limitations

The limitations of using AI for structured pedagogy arise from limitations in the use of AI for its constituent components, as well as from limitations in the systems required to align these components for effective structured

[6] onebillion's onecourse: https://onebillion.org/onecourse/. Retrieved 1 December 2025

pedagogy approaches. While curriculum-aligned, pedagogically sound lesson plans are an important tool for structured pedagogy, AI-generated lesson plans often exhibit linguistic mismatches, particularly when translated into local languages such as Kannada, for the Shiksha Copilot programme in India, with up to 94% of content requiring human editing for grammatical or semantic accuracy. Many lesson plans also lack visual aids (images, videos, or manipulatives) essential for science and mathematics instruction, as Large Language Model (LLM) systems are primarily text-based (↑Dennison et al., 2025).

While the use of AI can reduce lesson planning workloads for teachers in LMICs, non-instructional and administrative burdens persist, including data entry and clerical reporting (↑Dennison et al., 2025). In the EIDU DPL, structured pedagogy model, teachers played a critical role in managing the use of DPL devices and their transitions between learners (↑Plaut, 2024). Connectivity and infrastructure challenges further limit AI functionality; many Automatic Speech Recognition models are large, requiring cloud computing and cannot operate fully offline (on mobile phones), preventing instant feedback to students and localised processing, as demonstrated by the Early Grade Reading Assessment-AI (EGRA-AI) use case (↑AI For Education, 2024).

A further challenge lies in data availability and security. Many AI systems rely on detailed student and school-level data to maintain adaptive learning levels and coherence within structured pedagogy approaches, which are often inconsistent or unavailable in LMIC contexts. Even when data exists, limited technical capacity to manage and store large datasets restricts effective use. Moreover, information security risks arise when cloud-based models process data outside national borders, underscoring the need for clear standards and data governance protocols to ensure the safe and ethical use of the data (↑AI For Education, 2023; ↑UNESCO, 2021).

Summary of evidence

While the evidence base for AI-enabled structured pedagogy in LMICs is still emerging, **early results are promising**, particularly where AI tools are integrated into existing structured pedagogy programmes. The strong mid-line results from an RCT on EIDU's platform in Kenya indicate a positive impact on learning outcomes. Additionally, smaller-scale studies from India and Pakistan suggest improvements in instructional quality and early learning outcomes, with strong indications of **reduced teacher workload** and **enhanced pedagogical consistency**. However, the evidence on implementation remains limited, requiring more longitudinal and comparative research to determine sustained impact at scale (↑Sun et al., 2024).

Materials development

Quality educational materials are not a peripheral unit—they are part of the foundational infrastructure for learning. Teaching and learning materials are a core pillar of structured pedagogy programmes (↑Science of Teaching, 2024).

Randomised studies in Kenya and India have shown that merely providing high-quality textbooks and reading materials is not enough to improve learning; the material must match learners' language and proficiency levels. This illustrates the importance of contextual relevance and pedagogical quality over simple access to, and ample quantity of, educational learning materials (↑Glewwe et al., 2013).

Examples and evidence

While the Science of Teaching's structured pedagogy guides emphasise the importance of quality learning materials as part of the development of curricula and grade-level textbooks (↑Science of Teaching, 2024), evidence suggests the integration of AI for the development of learning materials has so far mostly been limited to adaptive or supplementary materials such as scripted lesson plans and contextualised lesson support; often in the shape of converting curriculum standards into engaging learning content (↑Aslam et al., 2025; ↑Srinivasan & Murthy, 2021).

RightToRead (India) leveraged the **Read to Me** AI engine to transform conventional curriculum content into a multisensory learning experience, integrating audio, visual, and contextual elements to enhance comprehension and engagement (↑Kim & Davidson, 2019). The programme reached more than 1 million students and 15,000 teachers across 5,000 government schools, achieving measurable learning gains through AI-driven content creation and adaptation. Studies reported a 20–40% overall improvement in learning outcomes across all proficiency levels, with continued *self-assessments* indicating even higher impacts of up to

50–60%, demonstrating the potential of AI-enabled multisensory content to strengthen foundational literacy at scale (↑Srinivasan & Murthy, 2021).

In **Senegal**, the Associates in Research and Education for Development (ARED) are partnering with Engeza to pilot an AI-enabled content pipeline that leverages local teachers and expertise to produce culturally relevant children's storybooks in six national languages. GenAI is being used to accelerate the development of the text and concept art, while human experts review and edit for linguistic accuracy, cultural fidelity, and appropriate learning levels. In this way, AI is being leveraged to support the development of high-quality instructional material that lends itself to the overarching structured pedagogy approach by aligning it with phonics phases, curricular targets, and weekly lesson sequences. Furthermore, this approach facilitates offline learning through the development of print-first copies to support read-alouds, guided practice, and home use (↑Asghar & Dintilhac, 2025).

Limitations

A key limitation to the use of AI for materials development is the lack of data in minoritised languages, as there are few resources for many local and indigenous languages, with limited annotated text, speech samples, and linguistic datasets required to train accurate AI systems. This gap reduces the effectiveness of online translation and adaptation tools, highlighting the need for institutional investment to safeguard linguistic and cultural diversity (↑Tsamo et al., 2024; ↑Zhao et al., 2024).

Another major constraint is teacher capacity and training. Many educators lack structured professional development on the ethical and effective use of AI, including generative AI applications. Without adequate training and continuous support, teachers are unable to fully leverage AI tools for pedagogy, content creation, or assessment, which limits their overall impact in classroom practice (↑Holmes & Miao, 2023; ↑Mohammed, 2023).

Summary of evidence

Although the development of high-quality materials begins with curriculum design and the creation of grade-level textbooks, current evidence on the use of AI for materials development focuses primarily on adapting more hands-on, classroom-level learning materials. As the technology is nascent and advancing rapidly, evidence on its use to support the development of high-quality learning materials comes from rapid studies and shows early signs of impact.

Evidence for AI's application in this focus area is supported by the way AI-driven interventions further established and *proven* approaches. For materials development, the evidence shows promise for the use of AI in contextualising and adapting existing high-quality materials and in democratising access to established pedagogical frameworks mastered over years of learning, training, and experience.

Language of instruction

Children should be taught in a language they understand (↑World Bank, 2021). There is such voluminous, consistent, and overwhelming evidence for this fact that it has been included in the United Nations Sustainable Development Goals (SDG) indicators:

SDG indicator 4.5.2 "*the percentage of students in primary education who have their home (or first language) as a language of instruction*" (↑UNESCO, 2016).

Yet, implementation remains challenging. According to UNESCO's Global Education Monitoring Report, more than a quarter of a billion learners globally—and up to 90% of learners in LMICs—do not receive education in their mother tongue, creating significant barriers to literacy and academic success (↑UNESCO, 2025b).

AI, with its natural language processing capabilities and capacity to be "trained on parallel data covering hundreds of languages", presents an opportunity to support the implementation of language-of-instruction principles in minoritised languages (↑Holmes & Miao, 2023; ↑UNESCO, 2025b). From the development of learning materials in local languages to the translation, adaptation, and contextualisation of available content, the use of AI can help reduce inequity and the digital divide and can make education more accessible, equitable, and inclusive (↑UNESCO, 2025a; ↑World Bank, 2021).

AI can operationalise mother-tongue instruction at scale by addressing resource gaps in translation, teacher language training, and localised content creation. Where policy and contextual constraints permit, AI can be used to support real-time translation and paraphrasing to bridge learning between the mother tongue and the medium of instruction (↑Holmes & Miao, 2023; ↑Tsamo et al., 2024).

Examples and evidence

Shiksha Copilot in India is a human-in-the-loop (HIL) AI system designed to support bilingual lesson planning in English and Kannada, promoting both content adaptation and inclusion. The platform leverages generative AI to help teachers create curriculum-aligned lesson plans efficiently. While the English lesson plans were considered highly reliable, the Kannada translations required extensive linguistic editing to ensure accuracy and natural phrasing. Importantly, teachers drew on their professional expertise and peer networks to refine and localise the AI-generated content, ensuring it remained contextually relevant and pedagogically sound. This example demonstrates the value of maintaining a collaborative human-AI approach, where teacher judgement enhances AI outputs to meet diverse classroom and linguistic needs (↑Dennison et al., 2025).

Another use case for AI-driven, diverse language-of-instruction support is the EGRA-AI assessment tool for foundational literacy. **EGRA-AI** (part of the ReadUp platform in South Africa) is an AI-powered Early Grade Reading Assessment (EGRA) tool that leverages Automatic Speech Recognition technology to assess oral reading fluency in isiXhosa. Focusing on translation and contextualisation, the team successfully developed a localised Automatic Speech Recognition model that achieved 95% item-level accuracy, demonstrating strong reliability in capturing reading performance in a low-resource language context. The AI-generated marking scores showed a very high correlation (0.99) with human assessors for items on which human raters agreed, indicating that AI can effectively complement traditional assessment methods when properly localised and validated (↑AI For Education, 2024).

Other examples include real-time oral reading checks and feedback in learners' languages provided by tools such as Pratham's **PadhAI** and Google's **Read Along** platforms (↑Asghar & Dintilhac, 2025).

Limitations

To leverage AI to support linguistic diversity in education, careful attention to *linguistic accuracy*, *cultural validity*, and *curriculum alignment* remains critical to sustaining gains in foundational literacy and numeracy.

A major constraint is the **lack of minoritised language data**, as many African and indigenous languages have few resources and lack annotated text, speech datasets, and other linguistic inputs needed to train accurate LLMs or online translation tools (↑UNESCO, 2021; ↑Zhao et al., 2024). This gap restricts the development of localised and culturally relevant educational content. Another concern is **bias and the reinforcement of dominant worldviews**: generative AI models, trained largely on mainstream and English-language data, tend to reproduce existing linguistic and cultural hierarchies, narrowing plural narratives and constraining the creation of diverse, locally grounded learning materials (↑Holmes & Miao, 2023). Finally, **dependence on infrastructure currently remains a barrier** to providing real-time feedback. The successful deployment of AI tools relies on stable electricity and internet access—both of which are inconsistent in many LMIC contexts—limiting teachers' and students' ability to reliably access AI-powered platforms and content (↑Molina et al., 2024). However, this challenge is mitigated by developing print-first content or by using offline features that can be synced when connectivity is available to leverage cloud-based AI processing (↑Asghar & Dintilhac, 2025).

Teacher professional development

In LMICs, teacher professional development (TPD) is often constrained by structural challenges—geographic isolation, resource shortages, inconsistent coaching, and high administrative burdens. These systemic obstacles limit teachers' opportunities for ongoing learning (↑D'Angelo et al., 2022). AI now offers a powerful mechanism to mitigate these gaps. By acting as scalable, adaptive mentors, AI systems can automate repetitive administrative work, provide tailored feedback, and support reflective pedagogical practice (↑Cukurova et al., 2024; ↑Shezad et al., 2025).

AI-driven TPD can move beyond traditional workshop models toward **personalised, data-informed, and practice-oriented professional learning**. Adaptive systems can identify a teacher's strengths and weaknesses, deliver just-in-time microlearning resources, and recommend pedagogical strategies aligned to specific classroom contexts (↑Chen et al., 2024). This individualised support can help teachers in LMICs gain real-time guidance, improve instructional quality, and sustain continuous professional growth.

However, integrating AI into TPD also demands a balanced approach. While automation can reduce cognitive overload associated with administrative and planning tasks, overreliance on AI for pedagogical reasoning may inadvertently deskill teachers by offloading critical thinking. Ensuring AI acts as a scaffold—supporting, not supplanting, teacher cognition—is essential (↑Caudwell & Mallaband, 2025; ↑Roy et al., 2024).

Examples and evidence

One of the earliest tools to leverage AI to assist teachers and support their continuous professional development is the **TheTeacher.AI**[7] tool. Deployed in Sierra Leone via WhatsApp, the tool was designed to provide teachers with subject-knowledge clarifications, lesson-planning assistance, and on-demand professional development support, all via a chatbot (↑Choi et al., 2023). While studies evaluating the use of TheTeacher.AI have found that most queries relate to content clarification (48%) and lesson planning (21%), the teachers preferred to use the chatbot for professional development guidance and instruction rather than web searches. Counterintuitively, teachers who leveraged AI in this way found it more cost-effective than web search because of lower mobile data transfer requirements (↑Björkegren et al., 2025).

GPTeach, an LLM-based platform, provides virtual coaching and practice simulations that let teachers rehearse classroom scenarios and receive immediate feedback, fostering iterative learning and skill refinement in a low-stakes, supportive environment. Similarly, **M-Power**, which leverages natural language processing, analyses classroom verbal interactions to generate automated feedback, guiding teachers in adjusting instructional strategies in real time and improving classroom discourse (↑Ortiz et al., 2025).

In addition to providing teachers with adaptive professional development support, there is a plethora of teacher assistant tools that leverage AI to reduce teachers' workload by providing prescriptive, contextualised learning materials, such as lesson plans and targeted assessments. Many have already been mentioned in this brief; others, including **Khanmigo, MagicSchool, TRCN-GMIND, TeachFX, Beaj Education**, and **ConveGenius,** are at different stages of pilot and implementation.

[7] http://TheTeacher.AI. Retrieved 1st December 2025.

Limitations

Despite its transformative potential, AI-enhanced teacher professional development presents several limitations that warrant careful consideration. A key concern is cognitive dependency and deskilling, whereby excessive reliance on AI for instructional decisions may gradually erode teachers' reflective and pedagogical reasoning abilities. Moreover, infrastructure and access barriers, including poor connectivity, limited device availability, and uneven digital literacy, continue to constrain adoption, particularly in LMICs (↑Caudwell & Mallaband, 2025).

Additionally, **ethical and privacy concerns**, such as algorithmic bias, opaque data use, and potential surveillance, threaten teacher trust and the equitable application of AI in education. Finally, there remain significant **evidence gaps** with few longitudinal studies demonstrating clear links between AI-supported TPD and sustained improvements in teaching practice or learner outcomes (↑Shezad et al., 2025).

Summary of evidence

AI-supported teacher professional development platforms show strong promise in improving instructional quality and teacher effectiveness in LMICs. Evidence from Shiksha Copilot, GPTeach, M-Power, TRCN–GMIND, and TeachFX indicates measurable reductions in lesson-planning time, enhanced lesson quality, and increased use of student-centred pedagogical strategies. Early findings suggest that these tools can scaffold reflective practice, support continuous skill development, and enable scalable professional learning. Yet, technology must not replace human agency. Only through blended models, ethical safeguards, human oversight, and competency-based frameworks can AI amplify teacher agency and nurture sustained instructional improvement.

Navigating what's ahead

The analysis of multiple use cases within the framework of the Science of Teaching, along with examples of products that exemplify these use cases, has led to an interesting insight: there is significant overlap between the AI tools leveraged and the AI functions fulfilled by these use cases across all the focus areas of Science of Teaching. This means that AI has the potential to play an effective role in accelerating the implementation of FLN practices, including by facilitating specific components of those practices. It also points to a logical conclusion: the development of a limited number of AI tools can lead to the implementation of applications across multiple proven practices that support FLN.

As we see the same products, tools, and functions overlapping across different aspects of education service delivery for FLN, we also see the same limitations that require focused consideration for the successful implementation of these AI-powered products and tools.

1. AI has the potential to be a cross-cutting enabler across the pillars of the Science of Teaching framework

The pillars of the Science of Teaching framework—such as *assessment-informed instruction*, *structured pedagogy*, *remediation*, *materials development*, *language of instruction*, and *teacher professional development*—are inherently interdependent, each reinforcing and enabling the others. Effective teaching is not a set of discrete tasks but an interconnected process where *assessment informs instruction* (↑Science of Teaching, 2023) and plays a critical role in *remediation* (↑Science of Teaching, 2022), *structured pedagogy* shapes the design and use of *learning materials* (↑Science of Teaching, 2024), and *teacher capacity* determines how effectively they are all implemented. Consequently, **an AI tool designed to support one proven practice naturally extends to others when well designed.**

As examples, we see the **Shiksha Copilot** in India and the **NIETE** platform in Pakistan, both designed to provide lesson planning support to teachers in multiple languages supporting *structured pedagogy* through expertly developed lesson plans that provide quality *learning materials*, in local as well as dominant *languages of instruction* and have *teacher professional* *development* courses built into them (to ensure effective use through digital literacy and pedagogical support) (↑Aslam et al., 2025; ↑Dennison et al., 2025). This interconnectedness means that robust, integrated AI systems can simultaneously amplify impact across multiple proven practices.

2. A limited few AI tools and capabilities can support multiple pillars of the Science of Teaching framework

A limited number of AI tools featured in the evidence base often support multiple pillars of the Science of Teaching framework because their core design functions—such as adaptive learning, generative content creation, data analytics, and natural language processing—naturally cut across several pedagogical needs. Rather than being narrowly specialised, these tools are built around fundamental AI capabilities that can be applied in various instructional contexts.

For instance, **Shiksha Copilot** uses LLMs and retrieval-augmented generation (RAG) to automate lesson planning (supporting *structured pedagogy*), generate assessments (*assessment-informed instruction*), and ease teacher workload while providing real-time professional support (*teacher professional development*) (↑Dennison et al., 2025). Similarly, EIDU integrates adaptive learning and analytics, enabling both personalised instruction (*remediation* and *assessment-informed instruction*) and consistent curriculum delivery (*structured pedagogy*). **Ei Mindspark**, designed for adaptive learning, simultaneously addresses *remediation* through individualised content and *assessment-informed instruction* through data-driven feedback loops.

This overlap occurs because effective AI systems respond to the interconnected nature of teaching and learning: **assessment insights guide pedagogy, pedagogy shapes materials, and teacher development amplifies both**. Thus, the same underlying AI capabilities—data analysis, personalisation, automation, and language generation—can serve different yet related instructional functions. The result is that even a small number of well-designed AI products can have multi-pillar applications, reinforcing multiple components of the Science of Teaching framework simultaneously and creating coherence across the teaching and learning process.

3. The limitations of the use of AI to support foundational learning in LMICs lead to opportunities in the form of mitigations

The constraints and limitations of leveraging AI to develop learning materials span ethical, pedagogical, technical, social, and economic domains (↑Holmes & Miao, 2023). It is important to consider these limitations when planning any AI-powered intervention and developing any AI-enabled tool.

Synthesising the evidence on the use cases of AI tools for FLN, we found that the use of AI to support foundational literacy and numeracy—through the evidence-based Science of Teaching framework—faces several limitations that span technical, pedagogical, linguistic, and contextual dimensions. Moreover, the limitations in implementing EdTech in general—such as infrastructure needs and teacher capacity—remain just as relevant when leveraging AI to support learning.

The table below summarises the key limitations of using AI for foundational learning and highlights the corresponding opportunities and mitigation strategies associated with each challenge.

Table 1. *Limitations to opportunities—Mitigations require human involvement*

Limitation		Opportunity in mitigation
Accuracy and reliability issues **Automated scoring and assessment tools** (e.g., CoBRA Pilot, EGRA-AI) often produce inconsistent scores, particularly for expressive tasks such as oral reading fluency (↑RTI International, 2022). AI models may underperform for mid-range learners or in spontaneous speech, reducing reliability as independent evaluators of student performance (↑AI For Education, 2023).	➔	**Human-in-the-loop (HIL) systems** Evidence emphasises the importance of keeping humans—especially teachers and content experts—at the centre of AI-supported processes. HIL systems ensure that teachers review and refine AI-generated assessments, lesson plans, or translations to maintain **pedagogical accuracy, contextual relevance, and cultural appropriateness** (↑Holmes & Miao, 2023). This approach was successfully demonstrated in the Philippines' **CoBRA pilot** and India's **Shiksha Copilot** project (↑RTI International, 2022).
Linguistic and contextual mismatch AI systems trained predominantly on English data struggle with **local or low-resource languages**, producing literal or awkward translations (as seen with Shiksha Copilot's Kannada lesson plans and **NIETE's** Urdu lesson plans) (↑Aslam et al., 2025; ↑Dennison et al., 2025). This limits accuracy and pedagogical usefulness, especially in multilingual LMIC contexts where instruction must be localised (↑Holmes & Miao, 2023).	➔	**Localisation and plurality** AI tools should support **local content creation**, **multilingualism**, and **crowdsourced contextual data** to counter linguistic bias and ensure cultural representativeness. Efforts like **African Storybook** and localised AI models that allow communities to contribute stories, voices, and language data—promoting inclusion and plural knowledge systems (↑Zhao et al., 2024). The development of open-source AI models trained on local languages is a significant step towards enabling developers and organisations to develop local language tools. Examples of such resources include *Masakhane*—a pan-African research collective, building open data sets and models for African languages—and the government of India's *Bhashini* service (↑Asghar & Dintilhac, 2025).

Limitation		Opportunity in mitigation
Teacher capacity, trust, and training gaps Teachers often lack adequate training to interpret and apply AI-generated insights, leading to mistrust or inconsistent use. Without proper support, educators may rely on AI outputs mechanistically rather than pedagogically (↑Choi et al., 2023).	→	**Teacher training and capacity building** Building teacher confidence and competence in the use of AI is presented as a critical mitigation strategy. The evidence supports comprehensive professional development, co-design processes involving teachers, and competency-based training that enables educators to interpret AI-generated insights and apply them meaningfully in classrooms (↑Holmes & Miao, 2023).
Overreliance and administrative gaps While AI can ease some administrative burdens (like lesson planning), teachers still face heavy workloads from unrelated bureaucratic tasks. There is also a risk of overreliance on AI systems without sufficient human review, which can lead to propagation of factual or contextual inaccuracies (↑Choi et al., 2023).	→	**Policy alignment and system strengthening** Governments and education systems are encouraged to adapt standards and accreditation frameworks to focus on competency-based outcomes rather than seat-time UNESCO measures. AI can also assist system actors—such as ministry staff—in summarising data, identifying trends, and generating reports, strengthening the broader education ecosystem (↑AMPLYFI, 2025).
Data and bias challenges The dominance of English datasets and Western epistemologies creates algorithmic and cultural bias, limiting the inclusivity of AI-generated content. AI systems can inadvertently reproduce inequities by favouring dominant worldviews and neglecting minoritised languages and perspectives (↑Dennison et al., 2025).	→	**Co-Design and prompt engineering** Teachers should be active co-creators in developing AI tools and learning materials, ensuring alignment with pedagogy and classroom realities. Additionally, training teachers in prompt engineering—the art of effectively interacting with generative AI—can improve the quality and relevance of outputs, thereby fostering ethical and reflective AI use (↑UNESCO, 2025b).

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