DIGITAL PROGRESS AND TRENDS REPORT 2025

Case Study 1

EXPLORING AI'S DISRUPTIVE PROMISE FOR EDUCATION SYSTEMS IN LOW- AND MIDDLE-INCOME COUNTRIES

WORLD BANK GROUP

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Sharada Srinivasan and Alex Twinomugisha

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Contents

Figure

Table

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Abbreviations

AI	artificial intelligence
GenAI	generative AI
LLMs	large language models
LMSs	learning management systems
LRLs	low-resource languages
MB	megabyte
RCT	randomized control trial
SD	standard deviation
SLMs	small language models
TAP	The Apprentice Project

Introduction

Realizing developing countries' demographic dividend requires investments in human capital through the provision of quality education. The benefits of demographic change for economic growth are mediated by educational attainment, with low-income countries standing to benefit the most (Kotschy, Suarez Urtaza, and Sunde 2020). Countries' historical experiences align; near-universal secondary school enrollment and quality educational provision were key to the success of East Asian countries in past periods of remarkable growth (Lutz et al. 2019). Investments in education also have important distributional implications. Education accounts for half of total economic growth and two-thirds of real income gains for people in the world's poorest quintile since 1980 (Gethin 2024).

However, education systems across developing countries are constrained by poor infrastructure and resources, and, as a result, they often struggle to ensure they have enough trained teachers and quality teaching and learning materials. Across developing countries, *learning poverty*—defined as the percentage of 10-year-olds unable to read and understand a simple text—has surged to an estimated 70 percent, even as primary school enrollment across countries has increased (World Bank et al. 2022). Secondary and post-secondary enrollment remains heterogenous across developing countries, with low enrollment in many (Local Burden of Disease Educational Attainment Collaborators 2020). Teaching quality and curricula vary, leading to developing countries' education systems unable to effectively match skills to labor market demand (UNICEF 2021).

Against this backdrop, artificial intelligence (AI) applications offer new possibilities. The AI tools used in education systems represent two distinct but increasingly convergent technological approaches. Classic AI systems include adaptive-learning platforms, intelligent tutoring systems, and early-warning dropout prediction models, and rely on structured data, explicit algorithms, and subject-specific customization over and above traditional educational technology. Research demonstrates their efficacy at scale in controlled settings (Muralidharan, Singh, and Granimian 2025), but classic AI tools can at times struggle to integrate with existing systems. In contrast, generative AI (GenAI) tools powered by large language models (LLMs) have seen rapid, often grassroots adoption by educators and learners. These tools work "out of the box" with minimal configuration, generating contextually appropriate content, explanations, and feedback through natural language interaction. Their flexibility often allows application across subjects, grade levels, and tasks, although outputs can vary in quality, and "hallucinations" are often a concern. The ease of use of GenAI tools has driven adoption independent of formal institutional decisions, with general-purpose GenAI platforms like ChatGPT being repurposed for educational use even in the absence of education-specific features.

AI applications can help support teachers in developing lesson plans and curriculum content or as virtual coaches and mentors working directly with students. They also can help personalize learning experiences to individual student needs, either through structured data (classical AI) or conversational-learning chatbots (GenAI). From early reading-fluency tools in primary schools to career guidance and skilling support in tertiary institutions, AI tools are being deployed at scale globally. As these tools proliferate across developing countries, questions emerge about their efficacy, equity, and, ultimately, their impact on learning outcomes in resource-constrained contexts.

Research on AI in education spans two distinct technological approaches with different evidence bases. Classic AI-powered adaptive-learning systems—which use machine learning to personalize content sequencing and difficulty based on student performance—have substantial research evidence. In contrast, research on GenAI tools—particularly LLM-based tutors—in education remains nascent, with most evidence limited to small-scale pilots.

- In Brazil, a randomized control trial (RCT) conducted in 178 public schools showed that AI-assisted grading improved student writing skills, with students writing 32 percent more practice essays and improving their grades by 0.09 standard deviation (SD) (Ferman, Lima, and Riva 2021). The education department in Brazil's state of Espírito Santo has since adopted AI writing evaluation tools for 30,000 students.
- Lesson plans designed with GenAI tools marginally improve pupils' career knowledge and confidence in the short run, when tested via an RCT in 18 low-income and government schools in Delhi, India (Anand 2024).
- An RCT in Ghana involving 1,035 students showed that an AI tutor (Rori) improved math achievement by 0.26 SDs after 6 months, with particularly strong effects for students who were initially behind their grade level (Henkel et al. 2024).
- In Nigeria's Edo state, learning improvements after a mere 6-week pilot using GenAI across 8 schools was about 0.3 SD, marking an improvement equivalent to nearly 2 years of typical learning (World Bank et al. 2022).

Given the widespread availability of general-purpose GenAI tools, accurately measuring the scale and effects of AI use across education systems in developing countries poses challenges. Evidence suggests that middle-income countries have disproportionately high adoption relative to their economic scale, contributing more than 50 percent of traffic to GenAI tools' websites (Liu and Wang 2024). Many day-to-day tools now come with embedded AI attributes—with adoption being by default rather than by intention—so actual use is difficult to measure accurately.

Although estimates in the United States suggest that nearly 60 percent of school leaders use AI for administrative tasks and 25 percent of teachers use it for lesson planning (Kaufman et al. 2025), similar data from most developing countries is unavailable. Small-scale surveys in various settings suggest varied adoption patterns (Björkegren et al. 2025; Arias Ortiz et al. 2025). However, an evidence gap persists in relation to nuanced dimensions such as users' experience with these new tools, the tools' perceived value, implementation barriers, and systemic constraints that shape how AI tools function in developing countries' education systems.

Qualitative research methods can shed light on how AI is being adopted in education systems and its potential effects, given the rapidly evolving state of play. Through in-depth interviews and focus groups, the deep dive presented in this case study aims to uncover the implementation of, barriers to, and perceived effects of AI—especially GenAI tools—in education systems in India and Nigeria. Both contexts are significantly heterogeneous: large federal states with significant variation in socioeconomic status, digital infrastructure capacities, and cultural attitudes toward new technologies.

Key research questions that this deep dive addresses include the following:

- How are developing countries' education systems implementing AI tools across educational levels (primary, secondary, and tertiary) and stakeholders (students, teachers, and administrators)? What are common patterns, as well as areas in which implementation modalities diverge from those observed in high-income countries?
- What are some challenges to AI implementation in educational settings in developing countries? How are countries working to ensure equity in access to new AI tools?
- How are teachers and students perceiving the effects of AI prevalence in their education systems? What are their perceived opportunities and concerns, as well as expectations about the future role played by AI-powered tools in education?

Methodology

This deep dive relies on in-depth interviews and focus-group-based, country-level consultations with a wide range of stakeholders—government officials, private sector individuals, civil society members, philanthropists, teachers, and school administrators. Consultations occurred between October 30, 2024, and February 2025 and lasted 45–120 minutes for in-depth interviews and 2–4 hours for focus groups and larger stakeholder consultations (refer to annex CS1A for the methodology and interview instruments). Nearly 60 in-depth one-on-one and small-group (fewer than 6 people) interviews were conducted using a standardized questionnaire, with semistructured follow-up interview questions. In addition, 3 focus group discussions (6–12 people each) and 1 larger stakeholder consultation at an Indian educational institution with approximately 150 people were conducted. These consultations were supplemented by desk research spanning the academic literature and relevant policy reports available online or shared by stakeholders.

The consultations covered urban and semi-urban areas primarily, with limited rural representation. In India, interviews and focus groups occurred in Bengaluru, Gujarat (Gandhinagar), New Delhi, and Telangana (Hyderabad), with virtual consultations for Indian organizations based outside of these cities. In Nigeria, consultations centered on Abuja and Lagos, with virtual consultations for organizations based outside these cities. Approximately 60 in-depth interviews were conducted with government officials, edtech company representatives and developers, civil society and think tank members, and educators (teachers and administrators). Three focus groups engaged approximately 30 students in tertiary education, teachers, and impact investors, collectively. One large stakeholder consultation, organized in Hyderabad, included approximately 150 participants comprising edtech companies' representatives, bureaucrats, students, teachers, and administrators. Given resource and time constraints, the sample does not have nationally representative coverage in either country, limiting generalizability to rural or less digitally connected contexts.

The artificial intelligence (AI) tools described in this case study reflect strategic selection and practical constraints and surfaced through our consultations for the case study. They are based on stakeholder availability and willingness to participate in our consultations rather than a systematic sampling of all AI education tools operating in India and Nigeria. Thus, the tools described should be understood as illustrative examples of AI implementation patterns in India and Nigeria rather than comprehensive inventories.

We base our usage data on stakeholder interviews and shared statistics; due to the private nature of many tools, we cannot verify these figures across all platforms. Claims about specific tool effectiveness, market penetration, or comparative advantages should be interpreted cautiously given selection bias toward more visible, well-resourced initiatives. While the focus of this case study was on trends and constraints that emerged across multiple interviews with diverse stakeholders, the individual tools classified in the case study represent accessible examples to ground these insights.

This deep dive is structured in three sections. The first section offers a taxonomy of AI tools being implemented at scale across two countries, India and Nigeria, with an emphasis on the differences and nuances in the development and implementation of these tools in the context of developing countries. The second section surfaces key insights from the consultations in India and Nigeria focused on three key aspects: infrastructure; the policy and regulatory environment; and the perceptions of developers, educators, policy makers, and students regarding these tools in the AI ecosystem. Finally, considering these findings, the last section provides recommendations for policy makers across developing countries.

An Emerging Taxonomy of AI Tools in Education Across Developing Countries

Introduction

Implementation of artificial intelligence (AI) tools in education across India and Nigeria varied by target audience and educational stage, with several new initiatives that leveraged generative AI (GenAI). In primary education, efforts focused on foundational literacy and numeracy—often, although not always—through teacher-mediated efforts. Private sector–led initiatives providing subject-specific and assessment-oriented tutoring applications directly to students were prevalent at the secondary level. Tools supporting teachers included lesson planning and content generation, assessment and feedback, and coaching of teachers for professional development. Across all levels, administrative support tools via intelligent learning management systems (LMSs), early-warning and dropout systems, and automation of key tasks relating to attendance and meal logging were observed.

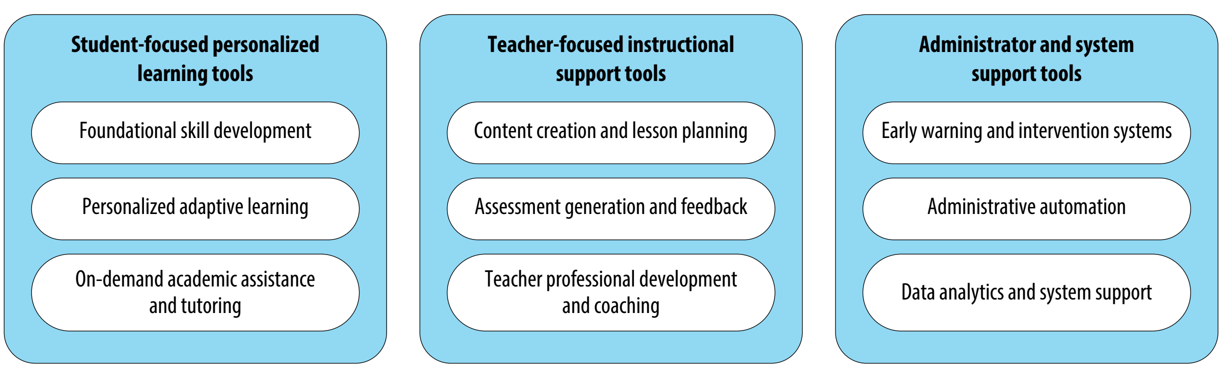
Figure CS1.1 describes the types of AI-powered tools that are being implemented at various levels of scale in India and Nigeria. The following section describes their specific characteristics with examples of tools in both contexts.

Student-focused personalized learning tools

Student-focused personalized learning applications could be classified as those focused on AI for foundational skill development, personalized adaptive learning, and on-demand tutoring.

At the primary education level, AI tools focus predominantly on foundational literacy and numeracy with emphasis on assessment and diagnostics. In the Indian state of Telangana, the AI strategy includes AI-based storytelling, speech recognition tools, and experiential approaches to

FIGURE CS1.1 Types of GenAI tools prevalent in education systems in India and Nigeria



Source: Original figure for this publication based on consultations with stakeholders.
Note: GenAI = generative artificial intelligence.

improve literacy and vocabulary. Wadhwani AI—a nonprofit organization—offers oral reading-fluency assessments in the Indian state of Gujarat, using AI to diagnose reading difficulties and track progress over time. The pan-Indian nonprofit EkStep Foundation is building mother-tongue literacy systems that assess student performance and provide diagnostic feedback to teachers, prioritizing learning in local languages. These tools are often scaffolded and teacher-mediated in elementary grades, with the AI providing real-time feedback on pronunciation, fluency, and comprehension that would be impractical for teachers to deliver individually across large class sizes.

The second category of tools focused on personalized learning pathways that adapt content sequencing and difficulty based on individual student performance. For example, the Khan Academy's Khanmigo leverages large language models (LLMs) to provide a more interactive, tutor-like experience and includes teacher-focused features (such as lesson planning, question generation, and exit slips) and learner-focused features (such as step-by-step solutions and concept prompts). The Khan Academy focuses on providing curriculum-aligned content for grades 6–12 and has medium-of-instruction content integrated with the systems in India's Maharashtra, Punjab, and Uttar Pradesh states. Khan Academy's implementation partners reported that approximately 35–40 percent of surveyed students admitted that AI feedback directly improved their exam performance. Some initiatives focused on special educational needs—for instance, Vinsighte's models focused on children with special educational needs and those with visual impairments by offering custom settings for users with attention deficit hyperactivity disorder, dyslexia, and other learning challenges, as well as offering audio translation.

Distinct from adaptive-learning systems that structure entire learning pathways, on-demand tutoring tools provide immediate assistance when students encounter specific difficulties. More prevalent at the middle- and secondary-school levels are tools focused on subject specialization, entrance exam preparation, and assessment support. Three organizations in India—Doubtnut, ConveGenius, and The Apprentice Project (TAP)—integrate AI to deliver content in regional languages across text, speech, and video, using WhatsApp.

Doubtnut—a doubt-solving app in which students can text questions to receive answers in text, speech, or video, saw widespread adoption among secondary students in India (handling 200 million queries per month). ConveGenius developed similar WhatsApp-based microlearning bots, attracting more than 1 million students within just 3 days during the coronavirus pandemic. ConveGenius later built a SwiftChat platform that now serves as an infrastructure layer for AI microservices across 21 Indian states, reaching 150 million learners and teachers. TAP's Buddy uses WhatsApp-based delivery mechanisms for personalized adaptive-learning modules in which students receive tailored difficulty levels, revision prompts, and reinforcement exercises based on their performance.

Student-focused platforms in Nigeria, such as uLesson and Simbibot, target individual learners with direct educational content, with both offering app-based online courses in secondary school subjects, AI-powered homework support, and entrance exam preparation tools.

At the postsecondary and tertiary education levels, nonspecialized, publicly accessible platforms dominate the GenAI landscape in both countries. In educational environments, students have cited OpenAI's ChatGPT (free tier) as a frequently used tool, with uses varying from support for projects to support with job seeking and skilling up in specific areas. Consultations suggest that widespread adoption in postsecondary education has occurred at least among those in urban and peri-urban areas with access to smartphones and laptops, in the absence of clear guidance and regulations, but not through education-specific AI tools or applications. Some specialized tools for career coaching are available, although they are not widely used.

Teacher-focused instructional support tools

Teacher-focused instructional support tools can be classified into three categories, including those for content creation and lesson planning, assessment and feedback, and teacher professional development and coaching.

In Nigeria, Schoola's Curri AI addresses content creation and lesson-planning challenges by helping teachers develop high-quality lecture materials tailored to local curricula and student needs. Gradely, reaching more than 3,500 teachers, empowers educators with personalized learning tools that can help improve student outcomes, in addition to direct student-facing products. Multilingual content generators have gained traction in India—including the EkStep Foundation's Assisted Math and Learning Program, developed in collaboration with AI4Bharat—enabling teachers to create materials in students' native languages and dialects. LLMs are being built by Awarri but have yet to be incorporated into the workflow of AI platforms offering teacher instructional support, which largely uses open-source models.

Assessment and evaluation tools that streamline grading processes for large populations were also prevalent. Automated assessment generators from Khan Academy's Khanmigo helps teachers create customized evaluation materials aligned with learning objectives and varying difficulty levels. ConveGenius evolved from early personalized adaptive-learning systems to sophisticated digital assessment platforms, integrating a psychometric and statistical analysis stack via acquisition of another company, Grey Matter.

Smart Paper provides teacher support through paper digitization as well as AI-powered assessment. The digitization component uses image processing to transform paper worksheets with multiple-choice answers into digital data with 95 percent accuracy or more, reducing what was previously a week of manual grading to approximately 5 hours of scanning and automated aggregation. This was valuable for large-scale government assessments, such as in the Indian state of Rajasthan, where 4.6 million papers were processed efficiently. A similar assessment mechanism is offered by a grantee of Co-Creation Hub's EdTech fellowship in Africa, Kuze.ai.

Recently, Smart Paper has expanded to include GenAI for grading descriptive assessments, allowing teachers to provide individualized feedback despite large class sizes. Some technologists at the Indian Institute of Technology Madras are exploring handwriting recognition and assessment and feedback with AI tools but note that such tools have not yet achieved accuracy.

Professional development tools with an emphasis on pedagogical skill enhancement rather than just-in-time content delivery are an emerging product. In India, Central Square Foundation is working on developing "teacher coaches" who provide personalized feedback on instructional approaches and classroom management techniques. Schoola's Curri AI also allows school administrators to review and provide feedback on teachers' lesson plans generated using AI.

Administrator and system support tools

Administrative AI tools vary in implementation and functionality across primary, secondary, and tertiary education. While GenAI tools demonstrate clear advantages in student-facing and teacher-facing applications, their role in administrative and system-level support remains more limited. Administrative tasks typically require structured data processing, integration with existing information systems, deterministic outputs for compliance and accountability, and auditability for which GenAI's probabilistic nature is not well-suited. As a result, where administrative AI tools are beginning to incorporate generative elements, they do so primarily for analytics and insight generation, such as for synthesizing data into reports for administrators, rather than for core operational functions.

In India, state administrations have widely adopted solutions that digitize routine administrative tasks that teachers traditionally perform manually. ConveGenius's SwiftChat handles administrative functions such as daily attendance tracking and midday meal program monitoring. These implementations feed into command-and-control centers such as Gujarat's Vidya Samiksha Kendra, where real-time administrative data can inform policy decisions at scale. Smart Paper similarly reduces administrative burdens through its digitization engine, processing millions of paper records that previously required weeks of manual data entry. These systems are valuable in resource-constrained settings where teacher time is limited and class sizes are large.

In Nigeria, administrative educational technology (edtech) tools that are beginning to integrate some elements of traditional AI have gained significant traction in the higher education sector. Edutech Global, a venture incubated in Vibranium Valley (a technology hub in Lagos, Nigeria), provides LMSs that increasingly use AI to manage processes and match students with appropriate courses at scale. This shift has enabled some Nigerian institutions to dramatically scale their offerings—enabling universities to grow from traditional campus-based models to serving more than 25,000 online students through distance-learning modes.

Other edtech companies such as FlexiSAF EduSoft provide comprehensive administrative solutions for more than 700 educational institutions, managing everything from student records to fee collection. These companies are also beginning to incorporate GenAI tools. In India, products targeting higher educational institutions have also incorporated predictive analytics into their dashboarding and data analytics workflows, generating insights from large amounts of data collected from students throughout their university journey.

Table CS1.1 provides detailed comparative information on the AI tools described in Figure CS1.1, showing their geographic distribution, educational levels, and key features.

TABLE CS1.1 Key AI or GenAI tools in India and Nigeria

Tool or platform	Country	Category	Primary users	Education level	Key features
ConveGenius	India	Adaptive learning, assessment, administrative functions	Students, teachers, administrators	Primary, secondary	WhatsApp-based microlearning, SwiftChat infrastructure for administrative tasks (attendance and meal tracking), integrated psychometric assessment (Grey Matter acquisition)
Doubtnut	India	Doubt-solving, tutoring	Students (direct)	Secondary, tertiary	WhatsApp-based delivery; regional language support (text, speech, and video); optimized for low-end smartphones; minimal bandwidth requirements
EkStep Foundation	India	Literacy tools, teacher support	Students (teacher-mediated), teachers	Primary	Ultra-lightweight models (40–50 MB), mother-tongue literacy systems, chatbots in local languages and dialects, Assisted Math and Learning Program with AI4Bharat
Khan Academy Khanmigo	India	Tutoring, teacher support	Students, teachers	Grades 6–12	Curriculum-aligned content for Maharashtra, Punjab, and Uttar Pradesh; medium-of-instruction integration; hybrid approach combining adaptive learning with GenAI tutoring
Mindspark	India	Adaptive learning	Students (teacher-mediated)	Primary, secondary	Offline mode, low-bandwidth design, local language support (Hindi and English), runs on basic tablets
Smart Paper	India	Assessment, digitization	Teachers, administrators	All levels	Paper digitization with 95% accuracy (image processing), AI-powered assessment for descriptive answers
The Apprentice Project's Buddy	India	Adaptive learning	Students (direct)	Secondary	WhatsApp-based delivery, personalized adaptive modules with tailored difficulty and revision prompts, regional language support
Wadhwani AI	India (Gujarat)	Reading-fluency assessment	Students (teacher-mediated)	Primary	Oral reading-fluency assessment tools, state government partnership
Awarri	Nigeria	Language models	Developers, educators	Not applicable	LLMs for low-resource Nigerian languages, not specifically for education; LangEasy crowd-sourcing platform for data collection

(Continued)

TABLE CS1.1 Key AI or GenAI tools in India and Nigeria *(Continued)*

Tool or platform	Country	Category	Primary users	Education level	Key features
Edutech Global	Nigeria	Learning management, administrative	Administrators, students	Tertiary	Classical AI-enhanced LMS for course management and student matching, beginning to incorporate GenAI
Gradely	Nigeria	Personalized learning, teacher support	Students, teachers	Primary, secondary	Personalized learning tool beginning to integrate GenAI
Kuze.ai	Nigeria	Assessment	Teachers, administrators	Primary, secondary	Digitization and assessment, developed with Co-Creation Hub's EdTech fellowship
Schoola's Curri AI	Nigeria	Content creation, lesson planning	Teachers, administrators	Primary, secondary	Lesson plan for teachers, review by administrators
Simbibot	Nigeria	Tutoring, homework help	Students (direct)	Secondary	App-based homework support and course content
uLesson	Nigeria	Tutoring, test prep	Students (direct)	Secondary	AI-powered homework support, entrance exam preparation
Vinsighte	Nigeria	Personalized learning	Students	Primary, secondary	Audio translation, visual impairment support

Source: Original table for this publication.
Note: AI = artificial intelligence; GenAI = generative artificial intelligence; LLMs = large language models; LMS = learning management system; MB = megabytes.

Distinctive Features of AI-Powered Educational Tools in India and Nigeria

Introduction

Artificial intelligence (AI) tools studied in India and Nigeria exemplify innovation under resource constraints and were developed with cost sensitivity as a design principle, piggy-backing where possible on existing platforms with large user bases (for example, WhatsApp). For instance, in India, organizations such as the EkStep Foundation are pioneering ultralight small language models (SLMs) of just 40–50 megabytes (MB) for local languages designed to run on basic devices with limited processing power. India's and Nigeria's implementations must function across dozens of low-resource languages (LRLs) with varying dialects—for instance, EkStep noted they must handle not just Tamil but also variations across regions such as Chennai, Kanyakumari, Madurai, and Pondicherry.

Nigerian initiatives demonstrate similar resource-conscious approaches. In Nigeria, Awarri has a partnership with the government to build large language models (LLMs) for LRLs, and it is working on specialized use cases in which smaller, targeted models can deliver significant value. These AI implementations enable cross-lingual capabilities that allow students to interact with educational content despite language barriers, thus efficiently using limited AI resources.

A critical question for policy makers is whether education-specific AI platforms add meaningful value beyond general-purpose tools like ChatGPT. Many platforms function primarily as "wrappers" around foundation models, adding interfaces and delivery mechanisms (such as WhatsApp integration) but limited pedagogical enhancement. However, implementations studied in both countries demonstrate substantive value-add:

- ConveGenius's psychometric assessment capabilities integrated with adaptive learning;
- EkStep's ultralight models (40–50 MB) optimized for low-resource devices and languages;
- Khan Academy's Khanmigo, which integrates curriculum alignment, learning progression tracking, and pedagogically designed prompting that do not directly provide answers; and
- Smart Paper's specialized digitization engine for processing handwritten assessments at scale.

Without these features, general-purpose GenAI tools may indeed match or exceed the educational value of bespoke platforms, raising questions about optimal resource allocation. Rigorous evaluations can help further determine which platform features justify investment versus cases where leveraging existing foundation models with appropriate guidance may be more cost-effective.

Data collection methods used to train models that then power AI tools used for education are equally as innovative. In India, university students are being mobilized to collect language data through programs such as AI in Telangana Internships, which has targeted 100,000 university students for such internships. Nigeria's Awarri has launched LangEasy, a crowd-sourcing platform that allows smartphone users to contribute voice and text inputs for model training. These approaches transform expensive data collection operations into community-driven initiatives that simultaneously build local AI capacity.

AI tools in both India and Nigeria are often specifically designed to function in contexts with low connectivity and intermittent electricity. Doubtnut's user interface is built for low-end smartphones, with minimal bandwidth, to empower learners in remote areas. Many tools offer offline capabilities, with data synchronization occurring only when connectivity is available, a feature rarely prioritized in other settings.

In Nigeria, several stakeholders noted the lack of high-quality access to the internet, necessitating solutions that operate on basic smartphones with minimal bandwidth, and power supply was mentioned as a major constraint in every interview. The Ministry of Education's distance-learning programs—which do not currently leverage AI but are exploring its viability for their platforms—rely on streaming based in school and community viewing centers to ensure adequate and equitable access to education in these settings, and content is delivered in a way that allows course material to be downloaded for offline use.

Teachers (primarily in tertiary education) interviewed in both countries reported using free-tier GenAI tools (such as ChatGPT and Claude) and adopting them to address administrative burdens, consistently noting they could complete lesson-planning and question-setting tasks more quickly. Teachers reported these uses freed time for more one-on-one student interactions, better classroom management, and building student-teacher relationships, especially with struggling learners. Notably, teachers did not report adopting AI for curriculum sequencing or pedagogical decision-making, emphasizing the need for their intervention and context-specific knowledge.

State governments in India and Nigeria have been pivotal to both piloting and scaling AI implementations through strategic partnerships and infrastructure investments. Organizations such as the Khan Academy have established formal partnerships with multiple state governments, including Maharashtra, Odisha, Punjab, and Uttar Pradesh, to integrate their platforms into state education systems. In Gujarat, Wadhwani AI's implementation of oral reading-fluency assessment tools reached statewide deployment with 3.4 million assessments—a scale made possible by the state providing digital infrastructure, including computer labs, tablets, and mandated classroom integration.

In Nigeria, a pilot in Edo State—conducted with support from the local state government—demonstrated the potential of integrating GenAI into education. The program engaged 800 secondary school students in after-school English sessions in which teachers facilitated student interactions with Microsoft Copilot.

The state's role extends beyond infrastructure to data governance. The EkStep Foundation noted that, in their partnership, the Indian state governments own the content, the data, and the deployment in schools, and technology providers handle the AI algorithms. This division of responsibilities allows state governments to maintain control over sensitive data while leveraging private sector expertise in AI development. Partners also noted that this arrangement allows states to create long-term AI integration strategies that can last beyond individual vendor relationships. State government partnerships were much more nascent in Nigeria, with most private sector actors directly engaging with schools and university administrations.

Constraints on developing and deploying AI tools in education

Although the evidence suggests that mother-tongue instruction tends to support academic development among children, AI development in non-Latin-script languages is a challenge. India and Nigeria are characterized by their linguistic diversity, but most local languages have insufficient digital resources. Of all internet websites, nearly half are in English, whereas fewer than 1 percent are in Indian or Nigerian languages (W3Techs 2025).

Unlike AI tools using English or other well-resourced languages, those serving students in languages such as Igbo, Yoruba, or Indian regional languages cannot leverage extensive preexisting datasets, although government-led efforts such as Bhashini in India and Awarri's Langeasy platform are starting to fill the gap. This data scarcity directly affects model performance, and research suggests that current multilingual LLMs have significant variability in performance when applied to LRLs (Zhong et al. 2024).

Language models tend to perform better with languages that use Latin scripts than with those that use non-Latin scripts, and non-Latin scripts are prevalent in most Indian regional languages, as well as in some Nigerian languages. Furthermore, available corpora in these contexts often have quality and coverage issues, because the data collected for these languages typically lack the annotation quality, scale, and domain-specific focus needed for educational applications. Education as a use case needs robust alternatives and high-quality data sets to ensure that model outputs do not hallucinate or generate misleading information, which may compromise learning outcomes.

The linguistic structures of many Indian and Nigerian languages present additional costs for training AI models and fine-tuning tools for education use cases, and these pose long-term costs. LLMs process and generate text sequences by splitting the text into smaller units, called *tokens*. English is the most token-efficient language, with the shortest median token length at 7 tokens. Bengali and Hindi, with non-Latin scripts, require approximately 5 times more tokens than English to express equivalent content.

This tokenization disparity has substantial practical implications: Developers building in these languages face greater context window limitations, higher operational costs, and increased processing times when using language models. Features such as nonlinear syntax in certain Nigerian languages or the complex morphological systems found in various Indian languages are also poorly accommodated by standard natural-language-processing architectures. Finally, in India, languages such as Bengali or Tamil can exhibit substantial regional variations, and in Nigeria, dialectal differences within languages such as Hausa can vary significantly across states. AI tools, therefore, require highly localized implementations, which can be costly and variable in accuracy.

Computer infrastructure limitations constrain the development of locally relevant AI models in both India and Nigeria. Nigeria's National Center for Artificial Intelligence and Robotics has identified computing infrastructure as a critical issue, highlighting difficulties in acquiring state-of-the-art graphics-processing units from producers. The absence of high-performance computing infrastructure forces difficult trade-offs between model capability and accessibility. These computing limitations disproportionately affect education applications in both countries, which need to handle pedagogical complexity in multiple languages and dialects and are often multimodal.

The feasibility of developing full-scale localized LLMs for dozens of LRLs thus faces significant technical and economic barriers that may make this approach unsustainable. Training separate foundation models for each language requires computational resources, expertise, and ongoing maintenance costs that exceed the capacity of most governments and education systems in developing countries. Current natural language processing architectures' tokenization inefficiencies compound these costs at both training and inference stages, making comprehensive LLM development economically prohibitive for many languages.

Two alternative pathways appear more viable in these contexts. First, ultra-lightweight models optimized for specific educational tasks rather than general-purpose language understanding show promise. EkStep's 40–50 MB models demonstrate that targeted applications—such as reading-fluency assessment or vocabulary building—can be achieved with dramatically smaller models that run on basic devices without cloud connectivity. These task-specific models sidestep the need for comprehensive language understanding while delivering educational value. Second, voice-first systems that bypass text tokenization entirely may offer more equitable access. Speech recognition and synthesis technologies can work directly with audio, avoiding the token multiplication penalty of non-Latin scripts. Voice interfaces are valuable in contexts with low literacy rates or for younger learners, and they reduce barriers related to keyboard layouts and orthographic complexity.

A third emerging approach combines multilingual foundation models with efficient fine-tuning techniques and prompt engineering in local languages, rather than building models from scratch. This leverages existing models' cross-lingual transfer capabilities while adding language-specific educational content and cultural context through relatively lightweight adaptations. The optimal pathway likely involves lightweight task-specific models for high-frequency educational functions, voice-first interfaces for accessibility, and fine-tuned multilingual models for complex reasoning tasks—all designed within the resource and infrastructure constraints of developing country contexts rather than attempting to replicate the full-scale LLM development pathways of high-income countries.

The cost structure of GenAI deployments fundamentally differs from traditional education technology investments in ways that are challenging. Most companies in Nigeria developing tailored AI solutions have suggested that they have used AI credits made available by big technology companies (such as Google or Microsoft) in developing their initial solutions; some were concerned that they would run out of these credits as they achieve scale in their deployments. Free credits have enabled proof-of-concept and early adoption with minimal capital expenditure. However, as platforms scale to thousands or millions of users, ongoing operational costs—primarily compute expenses for model inference—become the dominant cost factor.

Several Nigerian companies have expressed concern about sustainability once promotional credits expire, with no clear transition pathway to self-financing given the limited willingness to pay in education markets. In addition, cloud computing infrastructure was found to be expensive in Nigeria, in part because of its lack of a cloud on-ramp. The Nigerian government has suggested it is working toward building a sovereign cloud, promoting local data hosting, and attracting investment in local data centers, with the initiative in the early stages of implementation. Indian developers did not state that the cost of cloud computing was a predominant constraint, but its carbon intensity and cost to deploy were limiting factors, especially for larger or heavier implementations of AI-powered educational tools.

Inadequate last-mile infrastructure also creates deployment challenges for AI-powered tools. Intermittent electricity at schools and communities remains a fundamental barrier, with unreliable power mentioned by nearly every Nigerian stakeholder interviewed. Beyond power, connectivity issues create digital divides between urban and rural educational settings. Stakeholders in Nigeria noted that rural areas have little to no access to the internet or devices and even less access to reliable speeds even where internet is available. The hardware deficit compounds these problems, with many schools lacking basic computing devices.

These infrastructure gaps lead to a conundrum in which the students who might benefit the most from AI-enhanced education—those in underresourced schools—are precisely those facing the greatest barriers to access. Without addressing these fundamental infrastructure constraints, AI tools in educational settings risk exacerbating rather than reducing educational inequalities.

Policy and regulatory environment for AI use in education

The policy landscape governing AI tools in education remains underdeveloped in both India and Nigeria, creating uncertainty that impedes implementation. The ambiguity in guidance spans teacher roles, student evaluation methods, and acceptable boundaries for AI assistance in academic work. In India, stakeholders noted the lack of standardized AI frameworks for education as opposed to a nationwide policy, because the current environment makes it difficult to evaluate competing solutions or claims because of the proliferation of tools. Nigeria's Ministry of Education acknowledged the absence of AI-specific educational policies, although broader digital learning frameworks exist in the country.

Without clear guidelines, individual state governments and educational institutions reported struggling to make informed decisions about AI adoption. When government policies do exist, stakeholders noted that they often emphasize hardware procurement rather than substantive guidance on pedagogical integration, overlooking the importance of software quality and teacher training.

Data privacy and protection regulations remain inadequate to address the unique challenges posed by educational AI applications. Educational stakeholders in both settings—especially nongovernmental stakeholders—emphasized the lack of guidelines around data minimization or retention periods for student interactions with AI systems. The collection of student data through AI-powered educational tools raises significant concerns about consent, especially for minors who cannot provide informed consent themselves. In India, some state governments have defined data use clauses in contracts with partners and providers of AI-powered educational technologies, but the clauses vary in their strength of enforcement. Although Nigeria's National Information Technology Development Agency has adopted data protection approaches modeled after European standards, implementation gaps exist, particularly for educational settings.

Existing examination and academic integrity policies have not evolved to accommodate AI use, resulting in heterogeneous but poorly enforceable outright bans by educational institutions, especially at the tertiary education level. Many educational institutions have responded by prohibiting AI assistance rather than adapting to it, hindering the adoption of digital solutions based on concerns about critical-thinking development. The misalignment between legacy assessment policies and AI capabilities creates confusion for students and teachers alike about permissible AI uses in academic work. Stakeholders in Nigeria observed the need for revised assessment methods that prioritize critical thinking, but status quo policies at the individual institutions often were strict.

Perceptions of AI use among students, teachers, and policy makers

Teachers across India and Nigeria—at least in urban settings—have independently adopted AI tools for their teaching preparation, although they primarily use free-tier services. Most have taken the initiative to incorporate AI into their workflow by using general-purpose platforms such as ChatGPT to create classroom activities, and some are experimenting with more custom tools.

Subscription services remain financially out of reach for many education professionals in both countries. Teachers report significant efficiency gains from AI use in preparatory tasks and consistently note that AI produces higher-quality lesson plans more quickly than traditional methods. Many reported being able to complete planning tasks in minutes rather than hours, spending less time creating content and preparing lessons. Adoption of AI tools was observed despite the absence of formal requirements from the schools or the procurement of systems by private schools, reflecting their perceived utility.

Concerns that AI will stymie critical thinking dominate secondary- and tertiary-level teachers' and parents' perspectives on student AI use, whereas policy makers often report concerns about workforce readiness in the age of AI. Educational stakeholders observe that AI may also reduce curiosity and independent problem-solving capability. Professors report discouraging students from simply copying and pasting AI-generated content, and many universities use AI detection tools (that are often poor at detection) to screen student submissions.

In contrast, policy makers in both countries expressed an interest in preparing students for AI-infused workplaces. Government agencies highlight how AI-enabled assessment can be personalized and streamlined, and technology partners emphasize the importance of students becoming responsible AI consumers capable of innovation. This divergence in priorities—with teachers concerned about fundamental learning processes and policy makers focused on future workforce demands—creates tensions in determining appropriate classroom AI integration strategies.

Students, particularly those in tertiary education, have integrated AI into their academic workflow, raising concerns about skills development dependencies. Education technologists and researchers were optimistic about this change and observed that students use AI as a learning navigation system that helps them identify knowledge gaps and suggests personalized study paths. Others, such as Wadhwani AI, also noted that many students view AI as an essential productivity tool rather than merely an answer generator. However, this integration has prompted serious discussion among faculty about overreliance. Some felt that when students outsource cognitive tasks to AI, they risk failing to develop deep neural connections or genuine mastery.

In Nigeria, students in higher education and out-of-school science, technology, engineering, and mathematics learning environments report widely adopting AI for coding tasks, using these tools to accelerate programming and problem-solving. However, teachers and students alike reported growing concern about their ability to perform critical technical tasks without AI assistance. These observations were summed up by the EkStep Foundation, which calls this the "fallacy of fluency"—in which instant AI-generated solutions create an illusion of understanding without developing foundational capabilities. Balancing AI as a productivity tool while ensuring students develop core skills was posed as a key challenge by all stakeholders.

Policy Recommendations for AI in Education in Developing Countries

Introduction

A critical bottleneck for traditional educational technology adoption in developing countries has historically been diffusion, not innovation. There can be a "speed limit" on the adoption of artificial intelligence (AI) imposed by institutional realities rather than technological constraints. Well-established digital interventions such as short message service-based learning support, basic learning management systems, and digital content libraries have demonstrated impact (Angrist, Bergman, and Matsheng 2022) and yet rarely progress beyond pilot stages.

The institutional and market frictions that stalled earlier digital education efforts risk repeating with AI: procurement systems ill-suited to software-as-service models, teacher training systems unable to rapidly integrate new pedagogical approaches, and misaligned incentives where pilot success does not translate to resources for scaling. GenAI adoption through teacher-led grassroots use suggests demand exists, but translating individual adoption into systemic integration requires addressing structural barriers.

For successful AI integration in education, recommendations must go beyond technology-centric approaches, and make complementary investments in institutional, human capacity, and systemic challenges that have historically limited technology diffusion in developing countries. The following recommendations support the creation of enabling environments for experimentation and scale.

Define the educational problem before adopting AI solutions

Recommended actions include the following:

- Identify specific, measurable problems AI should address, such as teacher shortages, learning gaps at scale, assessment burden, or curriculum localization.
- Map problems to appropriate technological approaches, recognizing that not all educational challenges benefit from AI solutions.
- Establish success criteria before procurement. Define what improvement looks like (learning outcomes, teacher time savings, or student engagement) rather than measuring adoption rates.
- Create problem-solution mapping frameworks that education officials can use to evaluate whether AI is the right intervention.

Invest in people, not just technology: Teacher capacity as the foundation

AI tools are only as effective as the educators who implement them. GenAI's conversational interface lowers technical barriers but raises pedagogical complexity. Teachers may need training not in operating software but in designing effective prompts, evaluating AI-generated content for accuracy, and determining when AI assistance enhances versus undermines learning.

Recommended actions include the following:

- Develop comprehensive teacher professional development aligned with UNESCO's AI Principles and Competency Frameworks (Pedro et al. 2019), focusing on
    - Pedagogical strategies for integrating AI tools into instruction rather than just technical operation;
    - Critical evaluation of AI outputs for accuracy, bias, and appropriateness;
    - Adaptive teaching practices that leverage AI for personalization while maintaining teacher agency; and
    - Assessment literacy to understand when and how AI-generated evaluations should inform instructional decisions.
- Create peer-learning networks and communities of practice where teachers share implementation experiences and troubleshoot challenges.
- Provide ongoing support, rather than one-time training, such as mentorship systems, accessible help desks, and regular refresher sessions.
- Recognize that teacher adoption depends on demonstrating value. Prioritize tools that address teachers' most burdensome tasks (such as lesson planning, assessment creation, and feedback generation).

Reform procurement to enable innovation from start-ups and new entrants

Traditional procurement processes favor established companies and stifle innovation from start-ups often driving AI advancement. AI tools evolve so rapidly that traditional multiyear procurement cycles risk locking in outdated technologies.

Recommended actions include the following:

- Reduce barriers to entry for new companies.
    - Lower financial requirements for bid bonds and performance guarantees that exclude resource-constrained start-ups.
    - Accept proof-of-concept demonstrations and pilot results as qualification criteria rather than requiring extensive prior government contracts.
    - Allow consortium bidding where start-ups partner with established system integrators.
- Design procurement around outcomes and interoperability standards rather than prescriptive technical specifications that lock in incumbent approaches.
- Shift from large, monolithic contracts to modular procurement that allows best-of-breed solutions across educational functions.

Embrace experimentation, accept failure, and institutionalize learning

Given AI's rapid evolution and uncertain educational impact, governments must adopt experimental approaches. AI's rapid capability improvements mean evaluation results may become outdated quickly, requiring continuous rather than one-time assessment. The grassroots adoption of general-purpose AI tools also means governments are evaluating technologies already in use rather than controlling initial deployment.

Recommended actions include the following:

- Start with small-scale proofs of concept before systemwide deployment.
    - Pilot in diverse contexts (urban or rural, high- or low-performing schools, or different grade levels).
    - Set explicit decision rules upfront: What evidence would lead to scale-up versus discontinuation?
- Create safe spaces for failure.
    - Establish innovation sandboxes where experimental approaches can be tested with lighter regulatory requirements and protected funding.
    - Celebrate and publicize learnings from failed pilots to build collective knowledge.
    - Structure incentives so that piloting innovative approaches carries reputational benefit even when specific tools underperform.
- Institutionalize learning loops.
    - Require regular evaluation and public reporting on all AI education initiatives.
    - Build government capacity for evidence interpretation and adaptive management.
    - Use staged rollouts that incorporate feedback at each phase.

Address data and content gaps in local languages

Lead actors involved in addressing gaps include national governments (funding and coordination), private sector (technology), civil society and academic institutions (data collection), and development partners (financing).

Recommended actions include the following:

- Invest in systematic data collection for priority languages.
    - Fund crowd-sourced data-gathering initiatives, and provide credit for university students, micro-payments for community contributors, and so forth to diversify content.
    - Establish ethical frameworks, such as providing informed consent documents in contributors' native languages, creating community ownership of collected data, or prohibiting commercial uses without community benefit-sharing.

- Digitize existing educational content at scale.
  - Prioritize curriculum materials, textbooks, and assessments in languages spoken by the largest student populations.
  - Establish open educational resource repositories under Creative Commons licenses.
  - Create metadata standards enabling machine readability.
- Develop shared infrastructure for content creation.
  - Build and openly license small language models (SLMs) for educational content in priority languages.
  - Establish public-goods AI infrastructure such as compute resources and pretrained base models on which private developers can build.
  - Set open licensing requirements for publicly funded content.
- Design cost-sharing models.
  - Support government investment in foundational data and base models as public goods (similar to road infrastructure).
  - Develop partner cofinancing for regional language initiatives.
  - Encourage private sector contributions in commercially viable languages through tax incentives or research-and-development requirements.

Prioritize offline and SLM solutions for infrastructure-constrained settings

Given infrastructure constraints such as intermittent electricity, limited connectivity, and low-quality devices, offline-capable and SLM solutions are essential for equitable access.

Recommended actions include the following:

- Establish technical specifications for procurement.
- Provide innovation grants for models that may be viable in developing countries, such as
  - Ultra-lightweight educational AI models (under 100 megabytes [MB]),
  - Voice-first AI over 2G networks using Interactive Voice Response systems, and
  - Compression and optimization techniques for low-resource languages.

Establish data governance frameworks for educational AI

Educational data governance requires protections beyond generic data privacy regulations given student vulnerability. AI introduces several new considerations: AI systems collect far more detailed behavioral data than do traditional digital tools, AI derives insights about students that were not explicitly provided, AI's "black-box" nature makes it harder to explain how student data influences outputs, and data collected for education might train models used in noneducational contexts.

Recommended actions include the following:

- Adapt existing data protection frameworks with AI-specific provisions:
  - Extend data minimization principles to prohibit the collection of data unnecessary for immediate educational function.
  - Establish retention limits (for example, formative assessment data deleted after academic year).
  - Prohibit commercial use or sale of student data with criminal penalties for violations.
- Establish transparency requirements for AI processing:
  - Provide plain-language explanations of AI data uses that are accessible to parents with limited technical literacy.
  - Disclose whether student data trains broader AI models or remain confined to individual student profiles.
  - Explain the rights to access, correct, and delete personal data, with mechanisms enforceable within 30 days.
- Create oversight mechanisms without creating bottlenecks:
  - Support self-certification for low-risk AI applications (such as content generation and lesson-planning tools), with spot audits.
  - Use preapproval only for high-risk applications (such as predictive analytics affecting student placement and automated grading determining advancement).
  - Create rapid review processes (15–30 days maximum) so that governance does not prevent timely adoption.

Establish mechanisms for continuous policy adaptation in a rapidly evolving AI landscape

AI's rapid evolution creates challenges for education policy that traditional governance structures struggle to address. Benchmark standards may not keep pace with AI tools emerging weekly.

Recommended actions include the following:

- Adopt principles-based rather than prescriptive regulations:
  - Define desired outcomes (such as student learning improvement, equitable access, or data protection) rather than specifying technical requirements.
  - Establish clear prohibited uses (for example, AI-based student sorting or facial recognition without consent).
  - Create safe harbors clarifying which practices definitely comply, allowing actors to proceed without case-by-case approval.

- Create regulatory sandboxes for testing governance approaches:
  - Allow time-bound experiments (12–18 months) with lighter regulation to understand AI impacts before setting permanent policy.
  - Require rigorous evaluation and public reporting from sandbox participants.
  - Use sandbox learning to inform broader policy.

Conclusion

The path forward for both India and Nigeria lies in creating enabling environments with clear guardrails. By focusing on infrastructure-appropriate solutions, education-specific governance frameworks, local ecosystem development, responsible integration practices, and flexible innovation spaces, policy makers can harness the potential of artificial intelligence while addressing the unique challenges facing their education systems.

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Annex CS1A: Methodology and Instruments

Introduction

This study used a qualitative methodology that relied on snowball sampling for in-depth interviews, supplemented by focus groups and desk research, to examine artificial intelligence (AI) integration in education across India and Nigeria, combining rigorous qualitative research with extensive desk analysis to ensure findings were both robust and actionable.

The questions used in the semistructured interviews and focus groups are listed in the following sections.

Government officials

- What specific policies or guidelines has your government developed to regulate the use of AI in education?
- What AI-driven education initiatives is your government currently considering piloting and/or scaling?
- What are the country's long-term goals for integrating AI into education? How does AI fit into the national education strategy?
- How widely is AI, especially generative AI [GenAI], currently used in schools and educational institutions in your country/region?
- Are you monitoring or evaluating these initiatives' impact, and could you share some insights, if so?
- How are AI and GenAI being integrated into the (national or state) curriculum, what is your ministry's role in this process, and are there any partnerships formed? What kind of knowledge and skills should educational institutions prioritize to future-proof the students? What kind of skills are becoming less important?
- How is AI affecting the overall curriculum at elementary schools, secondary schools, vocational training schools, and universities? Has the education system in your country responded timely to changing technologies and labor demand?
- What strategies are being implemented to train teachers and educational staff in AI technologies, and what long-term plans does your government have for teacher training programs?
- How is the government ensuring the quality and reliability of AI-based educational content and assessments? How do you ensure that AI solutions and educational content are adapted to local languages and learning environments?
- Are there measures in place to ensure that AI tools used in education provide learning opportunities in areas with limited or no internet connectivity? If so, what are they?

- What is the government's approach to managing the data collected by AI tools used in education?
- Is AI being used to support students with disabilities or special educational needs? How?
- What are the key challenges you are facing or foresee in the long term for the use of AI in education?
- Are you collaborating with private tech companies or international organizations to implement AI in education? How are these partnerships structured at different stages of education?

Business leaders and edtech companies

- How are AI-driven tools being used in your educational products? Can you provide examples of how your company has successfully integrated AI into existing or upcoming products or services? What are the AI features in your products, and how do you use GenAI?
- What role does AI play in your company's strategy?
- Who are the main users of your products? Where are the users based—locally, nationwide, globally? Who are your main competitors? What is your comparative advantage?
- How do you ensure that AI-driven tools are adaptable to different educational systems and cultures? How versatile are your products?
- What challenges does your organization face in developing and using AI for educational purposes?
- How do you ensure the transparency and fairness of AI algorithms (with biases, data focused on specific populations) used in your educational products, and what steps are you taking to maintain these standards?
- How do you work with teachers and institutions to ensure that AI-driven tools meet their needs and expectations, and what partnerships have you established with educational institutions to codevelop AI-driven tools? How widely are your tools used by students and teachers? Trends over time?
- How does your organization measure the impact of AI on student learning outcomes?
- What initiatives are in place to train and support educators in the effective use of AI-driven educational tools, and how does your organization plan for the long-term sustainability of AI technologies in education?
- What new opportunities are you exploring to further innovate in this area?

Think tanks

- What role does your organization play in advancing the use of AI in education? Can you describe any ongoing or past projects your organization has undertaken related to AI in education? What were the key objectives?
- How do you prioritize and select areas or regions for implementing AI-driven educational interventions?
- What methodologies or frameworks do you use to assess the impact of AI in education? How do you ensure the collection and analysis of data remain ethical and representative across diverse demographics?
- Have you identified significant trends or patterns in the adoption and outcomes of AI in education through your research/product?

- Are there specific policy gaps you have identified that hinder the effective use of AI in education?
- What recommendations do you have for ensuring equitable access to AI tools in underserved regions?
- What kind of partnerships have you established with governments, edtech [educational technology] companies, or other NGOs [nongovernmental organizations] to implement AI-based educational projects?
- How is your interaction with teachers and students? What roles do they play?
- Are there examples of codesigned initiatives where local stakeholders had a significant role in shaping AI interventions?
- What strategies has your organization adopted to address biases in AI systems used in education? How do you ensure that AI tools are accessible to students with disabilities or those in remote, resource-poor settings?
- What challenges have you encountered in adapting AI tools to local languages and cultural contexts?
- Does your organization engage in capacity-building efforts for educators, policy makers, or researchers regarding AI in education? If so, how? What are your thoughts on the long-term sustainability of training programs for teachers and staff to use AI effectively?
- What emerging technologies or trends do you believe will shape the future of AI in education?
- What role do you see for your organization in driving innovation or scaling successful AI interventions in the coming years?
- How do you balance the promise of AI innovation with potential risks, such as overdependence or ethical concerns, in education?
- Who are key stakeholders in this space in your country, and why?
- What is your role currently with the state and nonstate actors?

Students

- Do you use AI, particularly GenAI, for learning/homework/any education-related purpose? What AI tools do you use? Are they provided by local companies or global edtech companies? Are they provided by school? How frequently do you use AI tools for education? Where do you use them, in school or at home? How do you feel about it?
- Do you pay for AI tools? How much do you pay? What is the maximum amount you are willing to pay for your most frequently used AI tool?
- How common is AI usage for education among your classmates and friends? Do you think you risk being disadvantaged if others use AI but you don't?
- Does your school or teachers allow AI usage in school/for homework/exams?
- Do your parents support you using AI tools for learning/education? If not, why?
- If you don't use any AI tools for education, why?
- How has AI affected your studying and completing assignments?
- What role do you think AI should play in providing feedback on your academic performance? How do you think AI could better help you with different learning styles or needs?
- How do you see the potential for AI to enhance your creativity and critical-thinking skills, and how do you feel about AI being used to grade or assess your work? Do you think you are

becoming highly dependent on AI? Do you think there is a risk of overdependence on AI, which could harm your writing/creativity/critical-thinking skills?

- How has AI affected your motivation or engagement in learning activities, and what support or resources would help you better understand and use AI tools in your education?
- What do you think the long-term impact of AI will be on your future education?
- Have you been involved in any AI-related projects or activities at school, and how comfortable are you with it? Do you think AI will potentially replace certain aspects of traditional teaching?
- How do you see the role of AI in ensuring equal access to educational opportunities? What kind of new tools do you think can help build that?
- How do you see AI influencing your future career choices or required skills, and how do you think AI could better prepare you for the challenges of the future, both academically and professionally?

Teachers

- How have you integrated AI into your teaching practice, and what impact has it had on your teaching methods and outcomes? If not, why? What AI tools do you use? Does your school require you to use it? How often do you use AI tools in your work? How useful do you find them to be?
- Do you allow students to use AI in homework or exams? Why or why not? How do you avoid letting students become too reliant on AI tools?
- Do you think there should be a minimum age for students to use [GenAI] tools like ChatGPT?
- How do you use AI-driven tools to personalize learning experiences for your students, and what challenges have you faced in integrating AI into your teaching?
- What training or support have you received to effectively use AI tools in your teaching?
- How has AI affected your ability to differentiate instruction for students with different learning needs, and what role does AI play in your approach to curriculum development and lesson planning?
- How has AI affected your workload and teaching efficiency? Has AI automated some tasks for you? How has AI affected your job satisfaction? How has AI changed your job/tasks/time allocation?
- How do you ensure that AI-driven tools are accessible and equitable for all students in your classroom, and what strategies do you use to monitor and evaluate these tools' effectiveness in improving student learning outcomes?
- How do you engage students in discussions about the use and impact of AI in their education, and how do you address student or parent concerns about the use of AI in the classroom?
- What potential do you see for AI to support students with special educational needs or disabilities? Have you collaborated with other educators or institutions to share best practices in using AI in education?
- How do you expect the teacher-student relationship to change as AI becomes more integrated?
- What role does AI play in your professional development, and how do you keep up to date with the latest AI tools and best practices for their implementation?

This case study, along with any associated content or subsequent updates,
can be accessed at https://hdl.handle.net/10986/43822.

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