International Journal of Emerging Issues in Social Science, Arts, and Humanities



https://ejournal.lucp.net/index.php/ijeissah

Original Article

IJEISSAH

Vol.4(4), October 2026, pp. 29-38
Published on 26 October 2026

ISSN Online: 2976-310X

Democratizing the Digital Frontier: Strategies for AI Literacy and Equity in Resource -Constrained Educational Settings

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DOI: *doi.org/10.60072/ijeissah.2026.v4i04.003*

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Received: 29 Jul 2026
Revised: 20 Oct 2026
Accepted: 23 Oct 2026

ABSTRACT

Artificial Intelligence (AI) is changing education systems worldwide at a rapid pace; however, unequal access to digital infrastructure, computational resources, and AI-enabled learning environments has widened what is now called the "AI Divide." In resource-constrained educational settings, students and institutions with limited access to advanced AI technologies risk being shut out of future academic and economic opportunities. This study investigates scalable and inclusive strategies for implementing AI literacy in low-resource environments, where high-cost infrastructure and high-speed internet connectivity remain out of reach. Drawing on a qualitative analysis of case studies on frugal innovation, policy documents, and open-source Small Language Models (SLMs), the research proposes a "Low-Bandwidth AI Literacy Framework" intended for equitable AI education. The framework gives weight to mobile-first pedagogy, hardware-agnostic tools, offline-capable AI systems, and critical AI literacy skills such as algorithmic auditing, ethical awareness, and prompt-engineering logic. The findings reveal that developing meaningful AI competency does not necessarily depend on premium generative AI platforms or advanced computing ecosystems. A foundational "Critical AI Agency" can instead be cultivated through pedagogical models that are decentralized, accessible, and ethically grounded. The study argues that democratizing AI education requires moving away from resource-intensive implementation and toward educational strategies that are sustainable, inclusive, and sensitive to context. Through the adoption of open-source and low-bandwidth AI ecosystems, educational institutions can promote digital equity, social mobility, and global educational inclusion in the age of Artificial Intelligence.

Keywords: Artificial Intelligence Literacy; Critical AI Agency; Digital Equity; Educational Technology; Low-Bandwidth Learning; Open-Source AI; Resource-Constrained Education; Small Language Models

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Background

Bringing Artificial Intelligence into educational systems is among the most significant pedagogical shifts of the 21st century. Adaptive learning platforms, intelligent tutoring systems, automated assessment tools and generative content engines are all changing how institutions around the world create, deliver and assess knowledge (UNESCO, 2023; World Economic Forum, 2023). This change, however, is far from uniform.

A growing body of literature points to a structural inequity in how educational technology spreads across the globe, one that is now hardening into what scholars call the "AI Divide" a stratification in which learners in high-income environments gain from sophisticated AI-augmented instruction while students in resource-constrained settings are increasingly left out (Selwyn, 2022; Williamson & Hogan, 2020). The divide is not only technological; it is deeply social, economic and geopolitical.

With AI becoming central to academic and professional ecosystems, students in resource-constrained educational environments risk being excluded from future opportunities. Such exclusion may deepen social inequality, limit participation in the workforce, and reduce educational mobility. Democratizing AI literacy has therefore become a global educational imperative.

This study examines how AI literacy can be implemented effectively in low-resource educational settings through approaches that are affordable, accessible, and sustainable. It explores open-source Small Language Models (SLMs), mobile-first pedagogies, and offline-capable AI tools as means of building inclusive learning ecosystems. Rather than stressing costly infrastructure or premium AI subscriptions, the research makes the case for decentralized educational strategies that put ethical awareness, critical AI thinking, and practical digital participation first.

The study develops a "Low-Bandwidth AI Literacy Framework" to help educational leaders, policymakers, and teachers bring AI education into underserved learning environments. The framework gives practical guidance on using accessible AI tools and methods that work around infrastructural and resource limitations, so that educators can design equitable learning experiences. With its focus on frugal innovation and educational equity, the framework aims to turn AI from a privilege of technologically advanced institutions into an educational resource open to all, thereby promoting student inclusion and digital empowerment.

With this background in place, the review of related literature below considers the AI divide, frugal innovation in education, emerging small language model ecosystems and the AI literacy frameworks that inform the present study.

Literature Review

The AI Divide in Global Education

The concept of the digital divide, first theorized in the late 1990s, has changed considerably now that algorithmic systems and machine learning dominate (Van Dijk, 2020). Early formulations focused on binary access to the internet, whereas contemporary analyses bring forward multi-layered inequities that span device ownership, data literacy, platform affordability and now, AI competency (ITU, 2022).

In India, this divide has several layers. According to the Annual Status of Education Report (ASER, 2023), 73.5% of rural households own a smartphone, yet only 26.2% of government upper-primary schools have

functional computers, and fewer than 15% have reliable broadband connectivity. There is a considerable gap between aspiration and infrastructure.

The AI skills gap in India carries significant economic implications. NASSCOM (2023) projects that India will be short of 1.4 million AI-skilled professionals by 2026. Because Tamil Nadu alone accounts for over 20% of India's IT exports (STPI, 2023), the capacity gap in school-level AI education has direct labour market consequences, and these fall disproportionately on students in government schools that serve Scheduled Caste, Scheduled Tribe, and economically weaker communities.

Whereas the AI divide brings out structural inequities in access and capacity, a parallel body of work points to frugal innovation as a route to more inclusive educational technology.

Frugal Innovation and Educational Technology

Core Principles of Frugal Innovation

Traditional innovation tends to depend on very large R&D budgets and high-end technology; frugal innovation, by contrast, follows these rules:

Cost Reduction: Removing "nice-to-have" features in order to concentrate on the essential core function (Radjou & Prabhu, 2015).

Robustness: Building tools that keep working in harsh environments (e.g., software that runs offline or on low-end smartphones).

Accessibility: Making sure the end product is affordable for the "bottom of the pyramid" (the poorest or most remote populations).

We should not delay teaching AI until every school has high-speed fibre internet and expensive devices.

India has a distinguished tradition of frugal innovation, that is, the deliberate design of solutions that remain affordable, simple, and robust under constraints (Radjou and Prabhu, 2015). Within educational technology, this tradition has produced models recognised internationally. The Pratham network's Teaching at the Right Level (TaRL) methodology was adopted in 11 Indian states and later replicated across Africa and Southeast Asia, and it shows that scalable improvements in learning can be achieved without high-cost technology (Banerjee *et al.*, 2016).

In Tamil Nadu, the e-Kalvi (e-Education) initiative of the early 2010s pre-loaded offline educational content onto shared computers in government schools, anticipating the "offline-first" design philosophy that now underpins frameworks such as Learning Equality's Kolibri. Under the ICT@Schools scheme, which was implemented across Tamil Nadu government schools with support from ELCOT (Electronics Corporation of Tamil Nadu), computer labs were set up in over 6,000 schools; utilisation studies (Subramaniam, 2019), however, indicate that these labs remain persistently underused because of gaps in teacher capacity and unreliable infrastructure.

More recently, the Naan Mudhalvan scheme, which the Tamil Nadu government launched in 2022, has embedded industry-linked digital and AI skills training for students in Classes IX–XII attending government and government-aided schools. Its partnership architecture, involving GUVI (Grow, Upskill, Vernacularise, and Innovate), NASSCOM, and Coursera, shows the potential of public-private frugal innovation in AI education at scale.

These frugal approaches intersect with emerging AI architectures, especially small language models able to run in low-resource environments.

Small Language Models and Offline AI Ecosystems

Recent progress in model compression, knowledge distillation, and quantization has substantially reduced the computational footprint of capable language models. Small Language Models (SLMs) such as Microsoft's Phi-3 Mini, Meta's LLaMA variants optimized for edge deployment, and Google's Gemma Nano can now deliver meaningful natural language processing on consumer-grade hardware with no internet connection (Gunasekar *et al.*, 2023; Touvron *et al.*, 2023).

This development has far-reaching implications for low-resource educational contexts. SLMs can be pre-loaded onto shared tablets, Raspberry Pi devices, or school servers, allowing offline AI interactions for language learning, question answering, and basic programming instruction. Just as importantly, because they demand less computing power, they consume less energy, which makes them compatible with solar-powered settings and places where electricity is intermittent.

Even so, how SLMs might be integrated pedagogically into low-resource classrooms remains undertheorized. Most existing literature deals with technical benchmarking rather than applied educational design, and this study seeks to address that gap.

In parallel with the technical development of small language models, scholars have put forward a range of AI literacy frameworks setting out what learners should know about AI and be able to do with it.

AI Literacy: Conceptual Frameworks

AI literacy has grown quickly as a field of educational inquiry and has produced a number of definitional and curricular frameworks. Long and Magerko (2020) propose a taxonomy of AI literacy competencies covering the recognition, application, evaluation, and ethical critique of AI systems. Touretzky *et al.* (2019) put forward a 'Five Big Ideas in AI' framework that is used in K-12 curricula in multiple countries.

The National Education Policy 2020 explicitly requires exposure to AI, machine learning, and data science from middle school onwards, and it calls for "computational thinking" to be integrated as a core competency at every school stage (MHRD, 2020). India's National AI Strategy (NITI Aayog, 2018), branded "AI for All", treats inclusive AI access as a national priority and identifies education as one of five strategic sectors.

A recurring criticism of mainstream AI literacy frameworks, however, is that they implicitly assume resource-rich contexts with full internet access, coding environments, cloud platforms, and adequate device-to-student ratios. This study argues instead for an alternative orientation that gives priority to 'Critical AI Agency': the capacity to understand, question, and engage purposefully with AI systems, even where access to technology is constrained.

Drawing on this literature, the study sets out specific objectives and uses a qualitative research design to develop a context-sensitive AI literacy framework for low-resource educational settings.

Objectives

The major objectives of the study are:

1. To examine the challenges involved in implementing AI literacy in resource-constrained educational settings.

2. To analyze how open-source Small Language Models (SLMs) contribute to democratizing AI education.
3. To investigate frugal innovation strategies suitable for low-bandwidth educational environments.
4. To develop a Low-Bandwidth AI Literacy Framework for inclusive AI education.
5. To explore the ways in which critical AI literacy can promote digital equity and social mobility.

In pursuit of these objectives, the study follows a qualitative, interpretivist research design that draws on document analysis, conceptual synthesis, and case study material.

Methods

Research Design

The research design is qualitative, resting on document analysis, conceptual synthesis, and case study evaluation.

Data Sources

The research utilizes secondary data collected from:

- Research articles on AI literacy and digital equity
- UNESCO and OECD educational policy reports
- Open-source AI documentation
- Frugal innovation case studies
- Educational technology reports
- AI implementation studies in developing regions

Method of Analysis

The study takes an interpretivist qualitative research paradigm, which suits the exploratory and context-sensitive nature of the inquiry. Its aim is not universal generalisation; instead, it seeks to produce conceptually rich propositions for AI literacy design in low-resource environments that can be acted on in practice.

Thematic analysis was employed to identify recurring themes related to:

- Accessibility barriers
- Infrastructure constraints
- Open-source AI deployment
- Mobile-first pedagogy
- Ethical AI education
- Inclusive digital strategies

The insights from this qualitative analysis were synthesised into a practical conceptual model, the Low-Bandwidth AI Literacy Framework, which is tailored to the constraints of low-resource educational environments.

Results and Discussion

Low-Bandwidth AI Literacy Framework

The proposed framework is intended to support the implementation of AI literacy in educational settings where technological infrastructure is limited.

Core Components of the Framework

1.Mobile-First Learning

In many underserved regions smartphones are easier to access than computers, so AI learning activities should be optimized for mobile devices. Accessibility can be improved through lightweight applications and AI tools that are compatible with mobile phones.

2. Offline-Capable AI Systems

Offline AI models make learners less dependent on a continuous internet connection. Lightweight Small Language Models (SLMs) can be installed locally on low-end devices for use in education (Gunasekar *et al.*, 2023; Touvron *et al.*, 2023).

3. Open-Source Ecosystem

Open-source AI tools are an affordable alternative to premium AI platforms (Gunasekar *et al.*, 2023; Touvron *et al.*, 2023). They allow localization and customization, and they support community-driven educational innovation.

4. Critical AI Agency

Students should learn not only how to use AI tools but also how to evaluate algorithmic outputs critically, identify biases, understand ethical implications, and engage with AI responsibly (Long & Magerko, 2020; Touretzky *et al.*, 2019).

5. Hardware-Agnostic Design

Educational AI systems should work on a range of device types, among them low-end smartphones, refurbished computers, and community digital centres.

6. Community-Based Learning

Access and sustainability can be widened through collaborative AI literacy initiatives that bring together teachers, local institutions, NGOs, and community centres.

Four high-impact frugal AI applications in use during 2025–2026 are described below:

1. The "Rori" Math Tutor (Low-Data Accessibility)

- An AI math tutor delivered entirely via **WhatsApp**.
- **Why it's Frugal:** It runs on any basic smartphone rather than needing a high-end app or a laptop. In 2026 its cost is only about US$5 per student per year, and in regions such as Ghana it yields learning gains equivalent to an extra year of schooling.

2. Offline "Small AI" (Infrastructure Independence)

- Using **Small Language Models (SLMs)**—such as specialized versions of Microsoft's Phi or Google's Nano—that are "compressed" so they can run with no internet connection.
- **Why it's Frugal:** It does away with the need for costly fibre-optic cables or constant 5G. Startups in **Bangladesh (e.g., Shikho)** are building these models into mobile apps that work entirely offline.

3. Voice-to-Text Literacy Tools (Hardware Agnostic)

- Thousands of schools in India use tools such as the **Oral Reading Fluency (ORF)** assistant.
- **Why it's Frugal:** It relies on the basic microphone of an inexpensive smartphone to listen as a child reads, then gives instant feedback and transcribes the data for teachers.

4. Raspberry Pi AI Servers (Low-Cost Hardware)

- Projects that use **Raspberry Pi** (tiny $35 computers) to run local AI models serving a whole classroom.
- **Why it's Frugal:** It takes the place of a $1,000 computer lab. A single "server" no bigger than a credit card can give a whole village school an AI-powered library and tutoring system.

The next section analyses how these core components respond to the documented barriers to AI access and literacy, and considers what they imply for equitable educational transformation.

The study's findings indicate that meaningful AI literacy does not necessarily depend on expensive infrastructure or premium generative AI subscriptions. Several low-cost, decentralized strategies can instead support AI education effectively in underserved environments.

Open-Source AI Expands Accessibility

Open-source Small Language Models substantially lower the barriers to adopting AI. Because they need less computing power, they can be deployed on low-resource hardware, which brings AI education within closer reach of economically disadvantaged institutions.

Mobile Learning Enhances Inclusion

Mobile-first educational strategies work especially well in regions where smartphones are more widely available than computers. AI systems compatible with mobile devices allow for learning that is flexible and scalable (ASER, 2023).

Offline AI Reduces Connectivity Dependence

AI systems that can work offline help with the problems posed by unstable or costly internet access. Students can use AI learning environments without having to stay connected all the time.

Critical AI Literacy Promotes Ethical Participation

When students are taught to evaluate AI-generated information critically, their digital citizenship is strengthened and their passive dependence on algorithmic systems is reduced. Ethical AI literacy supports responsible participation in technology.

Frugal Innovation Supports Sustainability

Affordable educational technologies, combined with decentralized implementation strategies, offer sustainable routes to integrating AI over the long term in low-resource settings.

Taken together, the findings suggest that equitable AI education calls for a move away from infrastructure-centric approaches and toward inclusive pedagogical and ethical frameworks.

From this analysis, the study arrives at several key findings about the conditions under which AI literacy can be meaningfully implemented in resource-constrained educational contexts.

AI literacy can be achieved without requiring advanced infrastructure. Schools can build important AI skills with mobile-friendly, open-source, and offline tools rather than costly cloud-based platforms.

Small Language Models enable offline, low-bandwidth AI learning. Running lightweight SLMs on shared or low-cost devices (such as smartphones, Raspberry Pi servers or refurbished computers) supports language learning, inquiry and basic help with coding, even where connectivity is intermittent or unaffordable.

A critical AI agency is as important as technical skills.AI literacy initiatives that put ethical awareness, bias detection, and the critical questioning of algorithmic outputs at the forefront help learners go beyond passive tool use towards responsible, reflective engagement with AI systems.

Frugal community-based implementation strategies enhance sustainability. Partnerships between schools, government schemes, NGOs, and local technology providers make it more likely that AI literacy initiatives in underserved regions will last over time.

A Low-Bandwidth AI Literacy Framework can guide equitable AI integration. The proposed framework gives policymakers, school leaders, and teachers a practical roadmap for designing AI literacy programmes that fit local infrastructural constraints while promoting digital equity and social inclusion.

These findings carry significant implications for the way educational systems, especially those in low-resource settings, design AI literacy policies, curricula, and professional development.

Conclusion

Artificial Intelligence could transform education across the world; yet unequal access to AI technologies threatens to deepen educational and socio-economic disparities. Educational settings with limited resources face significant challenges in infrastructure, connectivity, affordability and technical expertise. This study demonstrates that AI literacy can be implemented effectively through educational strategies that are decentralized, low-bandwidth, and open-source. With an emphasis on mobile-first learning, offline-capable Small Language Models, hardware-agnostic systems, and critical AI literacy, educational institutions can build inclusive AI learning ecosystems without relying on expensive technological infrastructure.

The proposed Low-Bandwidth AI Literacy Framework provides a practical, sustainable model for democratising AI education in underserved contexts. In the end, equitable AI education is not only a technological objective; it is a social responsibility essential to global educational justice, digital citizenship, and inclusive development.

Declarations

Ethics Approval and Consent to Participate: Not applicable. This study used only secondary data from published research, policy reports, and documentation; no human participants were involved and no personal data were collected.

AI Assistance: AI-assisted tools were used only for language editing; the authors reviewed all content and take full responsibility for the manuscript.

Conflicts of Interest: The authors declare no conflicts of interest.

Funding: This research received no external funding.

Authors' contributions: V. Vanitha conceived the study and led the writing; C. Prasanna Devi and B. Vinosha contributed to document analysis and revision. All authors approved the final manuscript

Acknowledgement: The authors thank the management and faculty of Fatima College (Autonomous) for their support and encouragement.

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