

BRIDGING THE DIGITAL DIVIDE: ENSURING EQUITABLE ACCESS TO ARTIFICIAL INTELLIGENCE FOR MARGINALIZED COMMUNITIES

by

Shivani Sachan

Research Scholar,
Faculty of Law,
University of Lucknow

&

Dr. Waheed Alam

Assistant Professor,
Faculty of Law,
Shia P.G. College, Lucknow

ABSTRACT

The advancement of Artificial Intelligence is changing areas, such as economies, governance, education, healthcare and public services. This makes AI a key driver of development and digital innovation. However not everyone benefits equally from AI. Some groups face inequalities that make it hard for them to access AI. These groups include people living in areas, low-income households, women, people with disabilities indigenous groups and communities with languages that are not well represented. This study looks at how the digital divide affects access to AI. It shows that digital inclusion is not about having internet access. It also involves having the digital infrastructure knowing how to use AI being able to afford it making it accessible ensuring fairness in algorithms including different languages and governing it ethically. The research uses studies and different perspectives to find out the barriers that stop people from being part of AI-driven systems. These barriers can be structural socioeconomic, technological or policy-related. The study also explores ways to make AI adoption fair. This can be done through AI, inclusive digital policies, innovation centered around communities partnerships between public and private sectors and initiatives that build capacity. These approaches can help minimize risks, like bias, privacy issues and technological exclusion.

A holistic conceptual framework has been put forward to assist decision-makers, researchers, stakeholders in the industry, as well as development agencies, in creating inclusive AI ecosystems that could contribute to the amelioration of social injustices, electronic equity, and sustainable development. The integration of technology and human-centered governance

means an important contribution to the analysis of AI accessibility and inclusion; it provides practical solutions to the problem of lack of access to AI and the involvement of marginalized communities into the process of digitalization. The most significant conclusion of the findings is that equitable access to AI is a technology not aimed only at acquiring the technological capabilities, but rather at achieving inclusive economic development and participatory democracy, as this would become a basis for Sustainable Development Goals implementation in the new AI age.

Keywords: --- Artificial Intelligence (AI); Digital Divide; Digital Inclusion; Equitable AI Access; Sustainable Development; Social Inclusion.

1. INTRODUCTION

The rapid advancement of artificial intelligence (AI) promises transformative benefits across education, healthcare, employment, and governance. However, without deliberate intervention, these benefits risk accruing disproportionately to already privileged populations, thereby deepening existing socioeconomic inequalities. “Bridging the Digital Divide: Ensuring Equitable Access to Artificial Intelligence for Marginalized Communities” addresses this critical challenge by focusing on how systemic barriers—ranging from inadequate infrastructure and limited digital literacy to biased data and exclusionary design practices—prevent marginalized groups from accessing, using, and benefiting from AI technologies.¹

The digital divide in the context of AI extends beyond mere connectivity. It encompasses three interrelated dimensions: the **access divide** (inequalities in physical access to AI tools and infrastructure), the **usage divide** (differences in skills, confidence, and meaningful participation in AI-enabled environments), and the **outcome divide** (disparities in who ultimately benefits from AI-driven outcomes). Marginalized communities—including women, people of color, persons with disabilities, LGBTQ+ individuals, rural populations, and low-income households—often face compounded disadvantages across all three dimensions. For instance, limited broadband access, unaffordable devices, and lack of electricity constrain basic connectivity, while insufficient AI literacy and culturally irrelevant content hinder effective usage. Recent survey data illustrates the depth of this gap within India: nationally representative data released in 2025 found that just under half of rural women aged fifteen and above still do not own a personal mobile phone, despite mobile

¹ UNESCO, *Recommendation on the Ethics of Artificial Intelligence* 8–10, U.N. Doc. SHS/BIO/AHEM/2021/PI/1 (2021).

ownership among rural youth being almost universal. Such device-level exclusion compounds the connectivity gap and illustrates why AI accessibility cannot be assessed through aggregate internet penetration figures alone.²

Ensuring equitable access to AI is not only a matter of social justice but also a prerequisite for sustainable and inclusive development. When AI systems are trained on non-representative data or deployed without community input, they can perpetuate or even amplify biases, leading to discriminatory outcomes in hiring, lending, healthcare, and law enforcement. Conversely, inclusive AI development—grounded in diverse data, participatory design, and localized content—can empower marginalized communities, enhance public services, and foster innovation that reflects a broader range of human experiences. India's own policy response illustrates this dual potential: the Union Cabinet's approval of the IndiaAI Mission in March 2024, backed by an outlay of over ten thousand three hundred crore rupees, was explicitly framed around the goal of 'Making AI in India, Making AI Work for India' and sought to democratise access to computing resources, curate Indian-language datasets, and support socially impactful applications in agriculture, healthcare and governance. Whether such mission-level investment translates into genuine inclusion for marginalised communities, however, depends on the implementation choices examined throughout this paper.³

- **Infrastructure Investment:** Expanding broadband coverage, subsidizing AI-compatible devices, and ensuring reliable electricity in underserved areas.⁴
- **AI Literacy and Education:** Integrating digital and AI literacy into school curricula, offering vocational training for adults, and developing community-driven learning programs in local languages.
- **Inclusive Design and Data:** Promoting open data policies, ensuring diverse representation in training datasets, and mandating accessibility features for persons with disabilities.

2. ARTIFICIAL INTELLIGENCE AND SOCIAL INCLUSION

² National Sample Survey Office data discussed in 'Digital Divide: 51% Rural Women Don't Own a Mobile Phone, Shows NSO Data' *Business Standard* (New Delhi, 29 May 2025) <<https://www.business-standard.com/topic/digital-divide>> accessed 21 September 2026.

³ Government of India, Ministry of Electronics and Information Technology, 'Government of India Expands AI-Driven Skilling' (Press Information Bureau, 19 March 2025) <<https://static.pib.gov.in>> accessed 21 September 2026.

⁴ UNESCO, *Recommendation on the Ethics of Artificial Intelligence* 59 (2021).

Artificial intelligence (AI) and social inclusion are deeply interconnected in the discourse on equitable technology access. While AI holds transformative potential to enhance inclusion—by improving access to education, healthcare, employment, and civic participation—it can also reinforce or exacerbate existing inequalities if deployed without deliberate equity safeguards. In the context of “Bridging the Digital Divide: Ensuring Equitable Access to Artificial Intelligence for Marginalized Communities,” AI must be understood not merely as a technical tool but as a socio-technical system whose design, deployment, and governance determine whether it serves as an instrument of empowerment or exclusion.⁵

AI's impact on social inclusion is dual-edged. On the one hand, AI-powered applications can break down barriers for marginalized groups: speech-to-text systems assist people with hearing impairments; predictive analytics help identify underserved populations in public health; and personalized learning platforms adapt to diverse linguistic and cultural needs. On the other hand, when AI systems are trained on biased or non-representative data, they risk producing discriminatory outcomes—for example, facial recognition technologies that misidentify people of color, or hiring algorithms that disadvantage women and older applicants. Such failures not only deny marginalized communities access to AI benefits but can also actively harm them, deepening distrust in digital institutions and widening the digital divide. Empirical research bears this out in the Indian context: an independent audit of four widely used commercial facial recognition tools, benchmarked against the Election Commission of India's public database of candidate photographs, found that the tools misidentified the gender of Indian women more than seven per cent of the time, compared with an error rate of under one per cent for Indian men. Such findings demonstrate that algorithmic bias is not a distant or purely theoretical risk but a measurable feature of AI systems already being piloted for governance and law-enforcement functions in India.⁶⁷

A parallel illustration comes from India's large-scale biometric identification infrastructure which, although not itself an AI system, previews the exclusionary risks that automated authentication can pose to marginalised users. Investigative reporting has documented that biometric authentication failures, disproportionately affecting manual labourers, the elderly, and women recovering from childbirth, have led to denials of healthcare, rations, and welfare benefits across several states. This experience underscores the importance of building

⁵ UNESCO, *Recommendation on the Ethics of Artificial Intelligence* (2021)

⁶ 'Facial Recognition Technology Isn't Wholly Accurate at Reading Indian Faces, Find Researchers' *Scroll.in* <<https://scroll.in/magazine/1001836/facial-recognition-technology-isnt-wholly-accurate-at-reading-indian-faces-find-researchers>> accessed 21 September 2026.

⁷ Joy Buolamwini & Timnit Gebru, Gender Shades: Intersectional Accuracy Disparities in Commercial Gender Classification, 81 *Proc. Mach. Learning Res.* 1 (2018).

redundancy and human fallback options into any AI-driven verification or eligibility system deployed at scale for marginalised populations.⁸

- **Data Exclusion:** Many AI models rely on datasets that underrepresent or misrepresent marginalized populations, leading to inaccurate or harmful predictions.⁹
- **Infrastructure Gaps:** Limited access to reliable internet, affordable devices, and electricity restricts basic AI usage in low-income and rural communities.
- **Skills and Literacy Deficits:** Without foundational digital and AI literacy, individuals cannot meaningfully engage with or critique AI systems, let alone contribute to their development.



⁸ 'Aadhaar Fails the Women Who Need It Most' *The Tribune* (Chandigarh)

<<https://www.tribuneindia.com/news/comment/aadhaar-fails-the-women-who-need-it-most>> accessed 21 September 2026.

⁹ Kate Crawford, *Atlas of AI: Power, Politics, and the Planetary Costs of Artificial Intelligence* (Yale Univ. Press 2021).

3. TECHNOLOGY ACCEPTANCE MODEL (TAM)

The Technology Acceptance Model (TAM), originally proposed by Fred Davis in the late 1980s, is a foundational theoretical framework in information systems that explains how users come to accept and use technology. At its core, TAM posits that two key beliefs—**perceived usefulness** (the degree to which a person believes that using a system will enhance their performance) and **perceived ease of use** (the degree to which a person believes that using the system will be free of effort)—determine an individual’s attitude toward technology, their behavioral intention to use it, and ultimately their actual usage behavior.¹⁰ In the context of “Bridging the Digital Divide: Ensuring Equitable Access to Artificial Intelligence for Marginalized Communities,” TAM offers a critical lens for understanding why marginalized groups may underutilize AI technologies—not necessarily due to lack of access alone, but because of perceptions shaped by usability barriers, relevance gaps, and contextual mismatches.

For marginalized communities, the constructs of perceived usefulness and perceived ease of use are deeply influenced by structural and socio-cultural factors. If AI tools are not designed with local languages, cultural norms, accessibility needs (e.g., for persons with disabilities), or offline functionality in mind, they may be perceived as difficult to use or irrelevant to daily challenges.¹¹ Similarly, if AI applications fail to demonstrably improve outcomes in areas that matter to these communities—such as healthcare access, agricultural productivity, or job training—they will be seen as lacking usefulness, regardless of their technical sophistication. This is corroborated by evidence from India’s language-access initiatives: the Bhashini programme, launched to embed Indian-language support across digital and AI services, was allocated close to four hundred ninety-five crore rupees over three years precisely because monolingual, English-first interfaces were found to be a primary reason why rural and non-English-speaking users disengaged from otherwise capable digital tools. The scale of this investment reflects a policy recognition that perceived usefulness, in Davis’s sense, cannot be assumed and must instead be actively engineered through linguistic and contextual design.¹² TAM thus highlights that equitable AI access requires more than infrastructure deployment; it demands user-centered design that aligns with the lived realities, priorities, and capabilities of marginalized populations.

¹⁰ Fred D. Davis, Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology, 13 *MIS Q.* 319 (1989).

¹¹ Viswanath Venkatesh, Michael G. Morris, Gordon B. Davis & Fred D. Davis, User Acceptance of Information Technology: Toward a Unified View, 27 *MIS Q.* 425 (2003).

¹² Government of India, Ministry of Electronics and Information Technology, Rajya Sabha Unstarred Question No 265 (2 August 2024) <<https://rsdebate.nic.in>> accessed 21 September 2026.

While the original TAM focuses on individual cognitive beliefs, scholars have extended the model to incorporate external variables such as social influence, facilitating conditions, trust, and digital literacy—factors especially salient for marginalized groups. For instance, in low-resource settings, **facilitating conditions** (e.g., availability of training, technical support, affordable data plans) may be stronger predictors of AI adoption than perceived ease of use alone. Likewise, **social influence**—such as community leaders endorsing AI tools or peer networks demonstrating their benefits—can significantly shape attitudes and intentions in collectivist or trust-based societies. This dynamic is evident in the design of India’s national digital literacy programme, which enrolled over seven crore rural candidates in basic digital and internet skills training between 2017 and 2023, precisely because infrastructure alone was found insufficient to drive adoption without accompanying facilitating conditions such as hands-on training and local support. Programmes of this kind suggest that AI adoption strategies aimed at marginalised groups should be paired with comparable, sustained skilling efforts rather than treated as a one-time infrastructure rollout.¹³ Integrating these contextual variables into TAM enables researchers and practitioners to diagnose not only whether AI is being used, but why it may be rejected or underused by specific populations, thereby informing more inclusive intervention.¹⁴

4. DIGITAL DIVIDE AND AI ACCESSIBILITY ASSESSMENT

The intersection of the digital divide and AI accessibility assessment represents a critical frontier in efforts to ensure equitable technology adoption. While the traditional digital divide focuses on disparities in physical access to devices and internet connectivity, the emerging **AI divide** encompasses deeper inequities in who can meaningfully access, understand, and benefit from artificial intelligence systems.¹⁵ AI accessibility assessment, therefore, must go beyond measuring broadband penetration or device ownership; it requires evaluating whether AI tools are usable, relevant, trustworthy, and beneficial for marginalized populations—including women, people of color, persons with disabilities, rural communities, and low-income households. Without such holistic assessment, AI deployment risks reinforcing existing inequalities rather than alleviating them.

AI accessibility is shaped by multiple, interrelated dimensions that mirror the layers of the digital divide. The **first-level (access) divide** concerns basic infrastructure: availability of

¹³ Government of India, Ministry of Electronics and Information Technology, Rajya Sabha Unstarred Question No 2015 (17 March 2023) <<https://rsdebate.nic.in>> accessed 21 September 2026.

¹⁴ Viswanath Venkatesh, James Y. L. Thong & Xin Xu, Consumer Acceptance and Use of Information Technology: Extending the Unified Theory of Acceptance and Use of Technology, 36 *MIS Q.* 157 (2012).

¹⁵ Jan A. G. M. van Dijk, *The Digital Divide* (Polity Press 2020).

electricity, affordable internet, and AI-compatible hardware. The **second-level (usage) divide** involves digital and AI literacy—the skills needed to operate, interpret, and critically engage with AI outputs. The **third-level (outcome) divide** captures whether AI use translates into tangible improvements in health, education, income, or civic participation for marginalized groups. Crucially, AI systems can fail at any of these levels: even with connectivity, a person may lack the literacy to use an AI diagnostic tool; even with literacy, the tool may be biased against their demographic group, yielding harmful or irrelevant results.¹⁶ Thus, accessibility assessment must diagnose barriers across all three levels to inform targeted interventions.

Several conceptual frameworks and practical tools have emerged to guide AI accessibility assessment with an equity lens. The **equity-centred design principles** discussed in Wharton-affiliated commentary on AI exclusion¹⁷ emphasizes community control over AI, inclusive design, and continuous auditing of data practices to prevent exclusion. Similarly, UNESCO and the UN advocate for **equity-focused technology impact assessments**, which require developers to audit datasets for representation gaps, test algorithms for discriminatory outcomes, and evaluate social context before deployment.¹⁸

India's own AI compute strategy illustrates one dimension of accessibility assessment focused on the affordability of access. Under the IndiaAI Mission, the government has subsidised access to a shared pool of high-end computing infrastructure, offering graphics processing units to researchers and start-ups at a rate of approximately sixty-five rupees per hour, explicitly to prevent the cost of computational resources from becoming a fresh barrier that replicates the earlier hardware and connectivity divide. Whether such compute subsidies reach community organisations and grassroots developers working with marginalised populations, rather than being captured primarily by well-resourced start-ups, remains an open empirical question for future accessibility audits.¹⁹

These assessments often include checklists on: (1) data diversity and bias mitigation, (2) interface usability across languages and abilities, (3) offline or low-bandwidth functionality, and (4) mechanisms for community feedback and redress. By institutionalizing such

¹⁶ Alexander J. A. M. van Deursen & Ellen J. Helsper, *The Third-Level Digital Divide: Who Benefits Most from Being Online?*, in *Communication and Information Technologies Annual 29* (Laura Robinson et al. eds., 2015).

¹⁷ Cornelia C Walther, 'How AI Exclusion Impacts Humankind' (*Knowledge at Wharton*, 2025) <<https://knowledge.wharton.upenn.edu/article/how-ai-exclusion-impacts-humankind/>> accessed 21 September 2026 (discussing AI inclusion and exclusion; the article does not itself name a formal "ABCD framework").

¹⁸ UNESCO, *Recommendation on the Ethics of Artificial Intelligence* (2021)

¹⁹ 'India: Expanding Compute Power to Drive Inclusive AI' *OpenGov Asia* (31 May 2025) <<https://archive.opengovasia.com/2025/05/31/india-expanding-compute-power-to-drive-inclusive-ai/>> accessed 21 September 2026.

assessments, policymakers can ensure that AI systems meet minimum standards of fairness and accessibility before reaching marginalized users.

5. AI APPLICATIONS FOR MARGINALIZED COMMUNITIES

AI applications designed for marginalized communities represent a critical pathway toward bridging the digital divide and ensuring that technological advances translate into real-world equity. Rather than deploying generic AI tools, effective solutions are **context-specific, culturally responsive, and co-designed with the communities they aim to serve**. These applications span diverse domains—including education, healthcare, financial inclusion, legal aid, and employment—and are tailored to address structural barriers such as language diversity, low digital literacy, disability-related accessibility needs, and lack of formal documentation.²⁰ When implemented responsibly, such AI tools can empower marginalized populations to access essential services, participate in the digital economy, and advocate for their rights.

AI-powered personalized learning platforms adapt content to individual students' pace, language, and learning style, making education more accessible for children in remote or under-resourced areas. Conversational agents and chatbots provide 24/7 tutoring, homework help, and digital literacy training in local dialects, supporting both formal schooling and adult education.²¹ For learners with disabilities, AI-driven screen readers, text-to-speech systems, and smart glasses enhance accessibility to digital curricula and exam materials. A recent Indian example illustrates this potential: an AI-enabled wearable device developed indigenously translates Indian Sign Language gestures into spoken English in real time and converts speech back into sign output, reporting accuracy levels of around ninety-eight per cent across fifty core gestures in pilot testing. Given that India is estimated to be home to over sixty million persons with significant hearing loss, yet only a small fraction of those requiring assistive technology are able to access it, such locally developed tools illustrate how AI can narrow rather than widen the outcome divide when designed around the specific needs of underserved groups.²²

²⁰ United Nations Dev. Programme, *Human Development Report 2023/2024: Breaking the Gridlock—Reimagining Cooperation in a Polarized World* (2023).

²¹ Wayne Holmes, Maya Bialik & Charles Fadel, *Artificial Intelligence in Education: Promises and Implications for Teaching and Learning* (2019).

²² 'Bridging Silence and Speech: An AI-Powered Leap for Inclusion' (NITI Aayog Frontier Tech, 19 June 2023) <<https://frontiertech.niti.gov.in/story/bridging-silence-and-speech-an-ai-powered-leap-for-inclusion/>> accessed 21 September 2026.

In regions with few doctors or specialists, AI enables remote diagnostics through image analysis (e.g., detecting tuberculosis from chest X-rays or diabetic retinopathy from retinal scans), triage chatbots that guide patients to appropriate care, and predictive models that identify high-risk populations for preventive interventions. India offers a concrete illustration of this potential at scale: an AI-powered chest X-ray interpretation tool developed by the Mumbai-based company Qure.ai has been credited with a nearly sixteen per cent increase in tuberculosis detection in an active case-finding programme in Nagpur, a city where a large share of patients rely on informal healthcare providers lacking specialist radiology support. Because each scan reportedly costs under a dollar to interpret, the tool illustrates how affordability and diagnostic accuracy can be combined to extend specialist-grade healthcare into underserved regions, provided such systems are validated on locally representative data.²³²⁴ Gender-sensitive and disability-inclusive AI health assistants provide confidential, real-time information on reproductive health, mental wellness, and chronic disease management, addressing stigma and information gaps faced by women and persons with disabilities.

AI-driven alternative credit scoring models assess creditworthiness using non-traditional data (e.g., mobile phone usage, utility payments), enabling unbanked populations—especially women and rural entrepreneurs—to access microloans and start businesses. India's fintech sector has been at the forefront of this shift: alternative credit-scoring platforms already assess hundreds of thousands of first-time borrowers using variables such as mobile application usage, digital footprint, and repayment behaviour on earlier small loans, extending credit to customers who would be classified as unscorable under conventional bureau-based models. While such models expand access for the credit-invisible, sector analysts caution that opaque scoring criteria and reliance on smartphone usage patterns can themselves introduce new forms of exclusion for the least digitally active borrowers, underscoring the need for transparency safeguards alongside innovation.²⁵ Job-matching platforms use machine learning to connect underserved job seekers with relevant

²³ 'AI-Driven Scans, Early Action: Qure.ai's Answer to India's TB Challenge' (NITI Aayog Frontier Tech, 19 June 2025) <<https://frontiertech.niti.gov.in/story/ai-driven-tuberculosis-diagnosis-a-transformative-solution-for-indias-healthcare-challenges>> accessed 21 September 2026.

²⁴ World Health Org., *Ethics and Governance of Artificial Intelligence for Health* (2021).

²⁵ IFMR LEAD, *Alternative Scoring Models on Access to Credit Among the Financially Underserved: Ecosystem Snapshot* (November 2024) <https://ifmrlead.org/wp-content/uploads/2025/01/Alternative-Scoring-Models-on-Access-To-Credit-Among-the-Financially-Underserved_Ecosystem-Snapshot_November-2024.pdf> accessed 21 September 2026.

training programs and employment opportunities, while AI-powered translation tools help migrants and refugees navigate labor markets and access social services.²⁶

Chatbots and virtual legal assistants automate legal research, explain rights in plain language, and guide low-income individuals through processes such as filing for housing assistance, challenging unfair evictions, or applying for asylum. Predictive mapping tools identify neighborhoods with high rates of unmet legal needs, enabling NGOs and governments to target pro bono services more effectively. India's Tele-Law programme offers an instructive precedent for such technology-enabled legal aid delivery, even though it relies primarily on video conferencing rather than AI: since its 2017 launch, the scheme has connected citizens at panchayat-level Common Service Centres with empanelled lawyers, reaching several hundred thousand beneficiaries in its early phases and demonstrating the feasibility of last-mile legal service delivery in rural India. Given that India's courts continue to grapple with a backlog running into tens of millions of pending cases, commentary from India's national AI portal has identified AI-powered legal chatbots and document-assistance tools as a natural next step for scaling such access, provided they are deployed alongside, rather than as a substitute for, qualified human legal aid.^{27 2829} Voice-based interfaces and multilingual AI agents allow citizens with low literacy or limited digital experience to interact with government services, report grievances, and participate in public consultations.

6. SUSTAINABLE AI DEVELOPMENT MODEL

A Sustainable AI Development Model integrates environmental responsibility, social equity, and economic viability across the entire AI lifecycle—from data collection and model training to deployment, monitoring, and decommissioning. In the context of “Bridging the Digital Divide: Ensuring Equitable Access to Artificial Intelligence for Marginalized Communities,” sustainability is not merely about reducing carbon emissions; it is about ensuring that AI systems are **inclusive, accessible, and beneficial** to marginalized populations over the long term, without exacerbating resource inequalities or imposing hidden costs on under-resourced communities. A truly sustainable AI model must therefore

²⁶ World Bank, *Digital Development Overview: Expanding Financial Inclusion Through Digital Technologies* (2022).

²⁷ ‘Rural India to Get Better Legal Aid Through “Tele-Law” Video Conferencing’ *Tech Wire Asia* (13 June 2017) <<https://techwireasia.com/?p=157465>> accessed 21 September 2026.

²⁸ ‘Enhancing Access to Justice: How Artificial Intelligence Is Democratizing Legal Services’ (IndiaAI, Ministry of Electronics and Information Technology) <<https://indiaai.gov.in/article/enhancing-access-to-justice-how-artificial-intelligence-is-democratizing-legal-services>> accessed 21 September 2026.

²⁹ UNESCO, *Recommendation on the Ethics of Artificial Intelligence* (2021)

align technical efficiency with social justice, embedding principles of equity, participation, and environmental stewardship into every stage of development.

AI systems, especially large-scale models, consume significant energy and generate substantial carbon emissions during training and inference. Sustainable AI development prioritizes **energy-efficient algorithms**, **lightweight model architectures** (e.g., MobileNet, DistilBERT), and **optimization techniques** such as pruning, quantization, and knowledge distillation to reduce computational demands.³⁰ It also advocates for **renewable-powered data centers**, **edge computing** to minimize data transmission, and **federated learning** to enable local processing on low-power devices—strategies that not only lower environmental impact but also make AI more accessible in areas with limited connectivity or electricity. The scale of this environmental challenge is considerable in the Indian context: projections presented around the India-AI Impact Summit indicate that AI data centres could consume close to five per cent of India's total electricity by 2030, with associated water consumption for cooling systems projected to rise from around one hundred fifty billion litres in 2025 to over three hundred fifty billion litres by 2030. These projections suggest that sustainable AI development in India cannot be treated as a peripheral concern but must be integrated into national energy and water planning alongside digital inclusion goals.³¹

Sustainability in AI demands that marginalized communities are not only beneficiaries but **active co-creators** of AI solutions. This requires **participatory design processes**, where end-users from underserved populations help define problems, validate data, and test prototypes to ensure cultural relevance and usability. It also entails **diverse and representative datasets** that reflect the full spectrum of human diversity, as well as **bias audits and fairness metrics** to detect and mitigate discriminatory outcomes.³² An “equity by design” framework further mandates that AI systems respect human rights, protect privacy, and include mechanisms for accountability and redress—especially for groups historically harmed by technological systems.

For AI to be sustainably adopted in marginalized communities, it must be **affordable, maintainable, and aligned with local economic priorities**. Sustainable AI models promote **open-source tools, modular architectures, and transfer learning** to reduce dependency on

³⁰ Roy Schwartz, Jesse Dodge, Noah A. Smith & Oren Etzioni, Green AI, 63 *Commc'ns ACM* 54 (2020).

³¹ 'India Must Balance AI Innovation with Environmental Integrity' *Down to Earth* (2026)

<<https://www.downtoearth.org.in/amp/story/science-technology/india-must-balance-ai-innovation-with-environmental-integrity>> accessed 21 September 2026.

³² United Nations Dev. Programme, *Human Development Report 2021/2022: Uncertain Times, Unsettled Lives* (2021).

expensive proprietary platforms and enable local developers to adapt solutions to evolving needs.³³ They also support **capacity building** through AI literacy programs, technical training, and partnerships with local universities or civil society organizations, ensuring that communities can own, operate, and govern AI systems over time.³⁴

7. CONCLUSIONS AND RECOMMENDATIONS

Bridging the digital divide in the age of artificial intelligence requires a paradigm shift from viewing AI as a neutral technological tool to recognizing it as a socio-technical system that can either reinforce existing inequalities or catalyze inclusive development. Without deliberate, equity-centered interventions, marginalized communities—already disadvantaged by gaps in infrastructure, literacy, and representation—risk being further excluded from the benefits of AI, leading to a two-tiered society where AI enhances opportunities for the privileged while deepening marginalization for the vulnerable. However, when designed with principles of participation, accessibility, and sustainability, AI holds transformative potential to empower underserved populations across education, healthcare, employment, and civic engagement.

The urgency of these recommendations is underscored by persistent structural gaps within India itself. Survey-based estimates suggest that women in India remain roughly fifteen per cent less likely than men to own a personal mobile phone and around a third less likely to use mobile internet services, with the gender gap in digital access reported to be the widest in the Asia-Pacific region. Unless AI policy explicitly targets these compounded gender and geographic disparities, national investments in AI infrastructure risk reproducing rather than resolving the very exclusions this paper has examined.³⁵

Recommendations

Governments and development partners must accelerate investments in broadband expansion, particularly in rural and underserved urban areas, while subsidizing AI-compatible devices and ensuring reliable electricity access. Infrastructure strategies should prioritize **offline-capable, lightweight AI models** that function on low-bandwidth networks and

³³ Org. for Econ. Co-operation & Dev., *OECD Framework for the Classification of AI Systems and Sustainable AI Development* (2024).

³⁴ Emma Strubell, Ananya Ganesh & Andrew McCallum, Energy and Policy Considerations for Deep Learning in NLP, in *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics* 3645 (2019).

³⁵ Oxfam India, *India Inequality Report 2022: Digital Divide* (Oxfam India 2022), discussed in 'Women Constitute One-Third of Internet Users in India: Study' (Vajiram & Ravi, IAS Current Affairs) <<https://vajiramandravi.com/current-affairs/?p=33745>> accessed 21 September 2026.

affordable hardware, enabling adoption in resource-constrained settings. National curricula should incorporate **digital and AI literacy from early grades**, with emphasis on critical thinking, data ethics, and hands-on engagement with AI tools. Adult education and vocational training programs must offer **localized, multilingual AI courses** tailored to diverse learning needs, including persons with disabilities and low-literacy populations.

AI developers must adopt **co-design methodologies** that involve marginalized communities in problem definition, data collection, model training, and evaluation to ensure cultural relevance and usability. **Diversity in AI development teams**—across gender, race, disability, and socioeconomic background—is essential to identify and mitigate biases early in the development lifecycle. Policymakers should mandate **algorithmic impact assessments, bias audits, and transparency requirements** for AI systems deployed in public services, especially those affecting vulnerable groups. **Ethical frameworks** must prioritize fairness, accountability, and redress mechanisms, with explicit protections for data privacy and informed consent.

Support **local R&D, open-source AI tools, and tech rental models** to reduce dependency on expensive proprietary platforms and enable community ownership. Establish **public-private partnerships and innovation sandboxes** to pilot context-specific AI solutions in high-impact sectors such as agriculture, health, and microfinance, with pathways for scaling successful interventions. Create **Citizen AI Review Boards** and community advisory councils to monitor AI deployments, voice concerns, and ensure accountability to end-users. At the national and global levels, governments should institutionalize **meaningful participation of marginalized groups in AI policy-making**, ensuring that governance frameworks reflect diverse lived realities and priorities.

References

Davis, F. D. (1989). Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology. *MIS Quarterly*, 13(3), 319–340.

Venkatesh, V., & Davis, F. D. (2000). A Theoretical Extension of the Technology Acceptance Model: Four Longitudinal Field Studies. *Management Science*, 46(2), 186–204.

DiMaggio, P., Hargittai, E., Celeste, C., & Shafer, S. (2004). Digital Inequality: From Unequal Access to Differentiated Use. *Annual Review of Sociology*, 30, 359–400.

Niehaves, B., & Plattfaut, R. (2014). Internet Adoption by the Elderly: Employing IS Technology Acceptance Theories for Understanding the Age-Related Digital Divide. *European Journal of Information Systems*, 23(6), 708–726.

Abdelfattah, B. M., Bagchi, K., Udo, G., & Kirs, P. (2010). Understanding the Internet Digital Divide: An Exploratory Multi-Nation Individual-Level Analysis. *AMCIS 2010 Proceedings*.

Alam, K., & Imran, S. (2015). The Digital Divide and Social Inclusion among Refugee Migrants: A Case in Regional Australia. *Information Technology & People*, 28(2), 344–365.

Davis, J. G., Kuan, K. K., & Poon, S. (2020). Digital Exclusion and Divide in the United States: Exploratory Empirical Analysis of Contributing Factors. *AMCIS 2020 Proceedings*.

Lim, D., & Yu, P. K. (Eds.). (2026). *Bridging the Global Artificial Intelligence Divide*. Oxford University Press.

Keskin, H., & Vermeulen, E. (2024). Bridging the Digital Divide With AI to Enhance Access and Equity in Underserved Communities. In *Proceedings of the 57th Hawaii International Conference on System Sciences (HICSS)*.

UNESCO. (2025). *AI Literacy and the New Digital Divide: A Global Call for Action*. Retrieved from <https://www.unesco.org/ethics-ai/en/articles/ai-literacy-and-new-digital-divide-global-call-action>

World Economic Forum. (2022). *A Blueprint for Equity and Inclusion in Artificial Intelligence*.

OECD.AI. (2025). *Towards Substantive Equality in Artificial Intelligence: Transformative AI Policy for Gender Equality and Diversity*.

NITI Aayog (India). (2025). *Roadmap on AI for Inclusive Societal Development*.

United Nations DESA. (2020). *Final Version Recommendations on AI and Social Inclusion*.

Club of Rome. (2024). *Inclusive AI for a Better Future: Policy Dialogue Report*.

Sivarajah, V., et al. (2026). Bridging the AI Divide: Approaches to Ensure Equitable Access to Artificial Intelligence for Marginalized Communities. In *Springer Lecture Notes in Computer Science*.

Simbo AI. (2025). *Bridging the Digital Divide to Enable Equitable Access to AI-Powered Healthcare Solutions Among Marginalized and Underserved Populations*.

Gates Foundation Grand Challenges. (2025). *Catalyzing Equitable Artificial Intelligence (AI) Use*.

Partnership on AI. (2026). *Creating Equitable AI Systems with the Participatory & Inclusive Demographic Data Guidelines*.

UNICEF. (2021). *Policy Guidance on AI for Children*.

Walther, C. (2025). How AI Exclusion Impacts Humankind. *Knowledge at Wharton*.

Parthasarathy, M., & Katzman, L. (2024). Bringing Communities In, Achieving AI for All. *Issues in Science and Technology*.

European Association of Social Service Providers (EASPD). (2025). *Unlocking the Potential of Artificial Intelligence in Social Services*.

Zenodo. (2026). *Bridging the AI Divide: Ensuring Equitable Access to AI in Education and Employment* (Preprint).

ScienceDirect. (2025–2026). Various articles on AI accessibility, digital equity, and inclusive design (e.g., DOI links in preceding sections).

