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Artificial Intelligence, Educational Access, and the Politics of Displacement: Structural Inequalities in Mobile Learning Contexts

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Abstract
The rapid proliferation of artificial intelligence within educational systems has generated considerable enthusiasm regarding its capacity to democratise learning, personalise instruction, and enhance administrative efficiency. Such optimistic narratives, however, frequently rest upon problematic assumptions: stable educational trajectories, continuous institutional membership, standardised learner profiles, and uninterrupted access to technological infrastructure. These assumptions collapse when examined against the lived realities of displaced populations—refugees, internally displaced persons, and migrants—whose educational experiences are fundamentally shaped by mobility, legal precarity, linguistic marginalisation, and fractured relationships with state institutions. This paper undertakes a critical examination of the intersections between artificial intelligence, education, and displacement, arguing that technological interventions designed without sensitivity to these structural conditions risk deepening rather than ameliorating educational inequalities. Drawing upon interdisciplinary scholarship from the sociology of education, forced migration studies, and critical technology research, this analysis situates AI-enabled educational initiatives within their broader historical, political, and institutional contexts. Particular attention is devoted to the Indian subcontinent, where diverse displaced populations navigate complex educational landscapes alongside the expanding reach of digital governance systems. The paper incorporates empirical insights derived from long-term sociological research on Tibetan refugees in India (Mishra, 2014), demonstrating significant intra-group heterogeneity in educational trajectories shaped by migration histories, institutional cultures, language regimes, and collective identity projects in exile. This analysis reveals that education in displacement contexts serves multiple social functions extending well beyond skills acquisition—including cultural preservation, identity formation, intergenerational transmission of historical memory, and the articulation of future-oriented political aspirations. The paper concludes by advancing a framework for AI-enabled educational governance that foregrounds contextual sensitivity, participatory design, equity orientation, and the preservation of human judgement in high-stakes educational decisions.

Keywords: Artificial intelligence; education; displacement; refugees; internally displaced persons; migration; sociology of education; digital inequality; algorithmic governance; India; cultural capital

Introduction: Situating AI In The Educational Governance Of Displacement

On a recent Tuesday morning, I came across three newspaper stories that sat uncomfortably alongside one another. The first, from the Times of India's Parenting supplement, asked whether AI was becoming 'the third parent' — a benevolent presence filling emotional and academic gaps for children whose busy parents could not keep up (Times of India, February 2026a). The second, from the same paper's Special edition, reported on research showing that large language models consistently assign high-status jobs to upper-caste names and mental labour to those associated with Dalit and Adivasi identities — a bias, researchers noted, that is particularly alarming given India's ambitions to host the AI Impact Summit (Times of India, February 2026b). The third was an op-ed by the Ukrainian envoy, marking the fourth anniversary of Russia's invasion: 'Our kids growing up without heat and stable schooling, displaced from their homes, will never forget' (Times of India, February 2026c). Three stories, three worlds. And yet the educational technology discourse in India — and globally — tends to address only the first.

This paper begins from the premise that these three stories belong together — and that the educational technology world has not yet understood why. We are living through two simultaneous global developments. First, AI is being built into educational systems at speed, promising personalised instruction, automated assessment, and administrative efficiency (Knox, 2020; McConvey & Guha, 2024). Second, forced displacement has reached a scale without modern precedent — over 117 million people currently uprooted by conflict, persecution, climate change, or development projects (Global Partnership for Education, 2024). Put these two developments together and the questions become urgent: what happens when AI systems designed for settled, documented, institutionally continuous learners encounter the realities of displacement? The scholarship has not kept up.

My central argument is this. AI in education can be useful — I am not arguing otherwise. But the risks are real and underacknowledged. When AI systems are deployed without serious attention to who is missing from their training data, whose documentation they assume, and whose educational goals they project, they do not simply fail to help displaced learners. They actively reproduce existing inequalities in a new technical form. The problem is not the technology itself. It is the set of assumptions baked into how the technology is built and for whom.

These are not abstract concerns. When an algorithm determines a child's learning level, sets their educational pathway, or flags them as at risk — and when that child is a refugee, an internally displaced person, a seasonal migrant — the stakes are concrete. Educational access for such children means far more than skills. It means psychosocial recovery. It means social belonging. In many cases it means cultural survival. Getting the governance of AI wrong in these contexts does not merely inconvenience — it forecloses.

I bring to this analysis three overlapping vantage points. The first is a research programme on Tibetan refugees — and, at M.Phil level, on Afghan and Tibetan refugee children comparatively — conducted over nearly three decades, including extended ethnographic fieldwork documented in my earlier monograph (Mishra, 2014) and continued through subsequent research and consultancy. The second is a formation in refugee protection spanning formal legal training in international humanitarian and refugee law (Indian Society of International

Law, 2001, supported by UNHCR and ICRC), an internship in UNHCR's Community Services and Protection Unit in New Delhi (2001), and over a year of professional work as Consultant and Social Worker at the Socio-Legal Information Centre (SLIC), New Delhi — an implementing partner of UNHCR (2002–03) — working directly with refugee communities on protection and socio-legal matters while simultaneously conducting M.Phil research. The third is close familiarity with India's evolving digital governance landscape — Aadhaar, the CAA, the NRC, the NEP 2020 — where the promises and failures of technology-led inclusion are visible in daily life and in the scholarly literature. I hope this combination of perspectives produces an analysis that is at once theoretically grounded and practically useful.

The paper moves as follows. Section 2 builds the theoretical framework — Bourdieu, Malkki, and critical technology scholarship. Section 3 provides the Indian policy and legal context: the Foreigners Act, the CAA, the NRC, the RTE Act, Aadhaar. Section 4 reviews the AI-in-education literature and names its blind spots. Section 5 looks at emerging practice globally and in India. Sections 6 and 7 address internal displacement and the governance politics of educational AI. Section 8 is the empirical core — my fieldwork with Tibetan refugees. Sections 9 and 10 draw out implications for design and press on the limits of automation. Section 11 offers policy directions. Section 12 concludes.

Theoretical Framework: Capital, Displacement, and Algorithmic Power

Three bodies of scholarship frame the analysis that follows. The first is Bourdieu's sociology of education, particularly his account of how cultural capital circulates unequally through institutions. The second is critical work on displacement and refugee studies, which insists on understanding forced migration as a structural condition rather than an exceptional one. The third draws on critical technology scholarship, asking what it means when AI becomes a mode of governance rather than merely a tool. None of these frameworks, taken alone, is sufficient. Together they let us ask the right questions.

Cultural Capital and Educational Inequality

Bourdieu's account of cultural capital remains indispensable for thinking about educational inequality. Capital, in his framework, takes three forms: embodied (the linguistic dispositions, aesthetic judgements, and taken-for-granted competencies we carry in our bodies); objectified (cultural goods — books, instruments, art); and institutionalised (credentials, qualifications recognised by official bodies). What schools do, in Bourdieu's analysis, is not neutrally measure merit. They measure how well a student's accumulated capital matches what the institution already recognises as legitimate (Bourdieu, 1986; Bourdieu & Passeron, 1990). This is a consequential difference.

For displaced people, this is not an abstraction. When you cross a border — or an internal administrative boundary — the cultural capital you have accumulated may simply not translate. Your credentials may go unrecognised. The languages you speak may mark you as foreign rather than competent. The cultural knowledge that earned respect in one setting becomes invisible or illegible in another (Erel, 2010). The school or the platform then encounters what looks like underperformance. It is not underperformance. It is a structural mismatch between accumulated capital and institutional expectation.

This is precisely where AI systems create a new problem. An adaptive learning algorithm trained on data from mainstream educational settings will encode particular forms of cultural capital as normal. The student whose competencies look different — whose literacy was built in a different script, whose analytical style reflects a different pedagogical tradition — will be measured against a standard that does not fit them. The result is not a neutral assessment. It is a bias embedded in architecture. Recent empirical work confirms that algorithmic systems in education do exactly this: they reproduce and amplify existing disadvantages, doing so through processes that appear technical and therefore objective (Baker & Hawn, 2021; Gándara et al., 2024).

Displacement as Structure, Not Exception

Liisa Malkki's (1995) critique of the 'national order of things' remains one of the most important interventions in refugee studies. Her argument was simple and devastating: when scholars and policymakers treat refugees as persons out of place — anomalies in a world that should be organised by matching people to national territories — they obscure the political processes that produce displacement in the first place. Displacement is not an exception to normal life. It is produced by the same states and political economies that claim to be normal.

When you extend this argument to education, something important follows. Displaced learners are routinely positioned as exceptions to systems designed for someone else — beneficiaries of emergency programmes, problems to be managed, populations requiring special modules rather than full institutional inclusion. AI systems replicate this logic when they are designed for 'normal' learners and then retrofitted for displaced populations. The displacement is treated as a technical problem. In fact, it is a political one, and no technical fix will substitute for addressing it at that level.

What fieldwork teaches — and I have learned this over three decades of research — is that 'refugee' and 'IDP' are homogenising categories that conceal enormous internal variation. Class, gender, prior educational attainment, migration route, legal status, length of displacement, language, age: all of these interact to produce educational experiences that differ radically from one person to the next (Dryden-Peterson, 2011). I return to this at length in Section 8, drawing on my own fieldwork. The point here is that any AI system designed around a generic 'displaced learner' profile will fail most of the actual people it is supposed to serve.

South Asian scholarship on displacement has produced some of the most rigorous structural analysis in this domain. Ranabir Samaddar's edited volume on refugees and the state — spanning 1947 to 2000 — documents something that remains true: India's hospitality to displaced populations has always been simultaneously generous and controlling (Samaddar, 2003). The state extends welcome and exercises power over those it welcomes. His later work situates this within broader patterns of transborder movement, labour migration, and statelessness that have defined the subcontinent since Partition (Samaddar, 2020). Paula Banerjee's work on internal displacement and gendered border existences is equally necessary — it makes visible the compound vulnerabilities that women and girls in displacement face at the intersection of mobility, patriarchy, and state indifference (Banerjee, 2005; 2010). Neither framework is optional for anyone working on AI and education in India. Without them, the analysis is borrowed rather than grounded.

Algorithmic Governance, Caste, and Digital Exclusion

The third pillar draws on critical technology studies. Noble (2018) and Benjamin (2019) have made the core argument convincingly: AI systems are not neutral tools. They are forms of governance. They make decisions — or structure the conditions under which decisions are made. And they encode values: in the data selected for training, in the features engineered, in what counts as success, in what gets flagged as risk. These choices are made by humans, reflect existing social arrangements, and carry consequences for the people the systems touch.

The India-specific finding I find hardest to set aside concerns caste. Research published in early 2026 tested what happens when large language models — GPT-4o, GPT-3.5, LLaMA variants — are asked to assign jobs to people with different names (Times of India, February 2026b). The results were consistent across models: upper-caste names received high-status, knowledge-economy roles. Dalit and Shudra names were directed toward manual and service work. The researchers called this stereotype reinforcement at a structural level. For this paper, that finding is not peripheral — it is central. If the language models underpinning educational AI in India encode caste hierarchies as their default, then deploying those systems in schools serving displaced, Dalit, or Adivasi children is not democratisation. It is discrimination in a new technical form.

Displaced populations face compounded risks from algorithmic governance. Their data is scarce and fragmented — they are underrepresented in training sets, so models perform worse for them (Gándara et al., 2024). Documentation gaps mean exclusion from systems requiring verified identities. Educational histories interrupted by displacement get misread as evidence of low ability rather than structural circumstance. Aadhaar — India's massive digital identity programme — shows the pattern clearly: intended to include, it has produced a well-documented set of exclusion errors for people whose biometrics fail, whose documents don't match, whose addresses are not fixed (Panigrahi, 2021; Khera, 2019).

Intersectionality and Compound Marginalisation

Intersectionality matters throughout this analysis. Displacement does not arrive alone. It combines with gender, caste, class, language, disability, and generation to produce experiences that differ dramatically from one person to the next. Displaced women and girls carry particular burdens: interrupted schooling, domestic expectations, heightened vulnerability to gender-based violence, systematic exclusion from opportunities that patriarchal settings reserve for men (Brookings Institution, 2020). Children with disabilities in displacement settings face compound disadvantage that generic technological responses will not reach.

My own sustained research on Tibetan refugees in India has been concerned with exactly these intersections (Mishra, 2014). What I found, and what I believe holds more broadly, is that displaced learners are always navigating two things at once: their individual educational trajectory and a collective cultural or political project that their community has invested in education to carry. Standard institutional metrics — and AI systems built on those metrics — will see only the individual. They will miss the collective. And missing the collective is missing the point.

Historical and Policy Context: Education, Displacement, and Digital Governance in India

India is a particularly important context for this argument — not because it is exceptional, but because it concentrates so many of the relevant dynamics in one place. The subcontinent has hosted displaced populations for over six decades: Tibetan refugees since 1959, Sri Lankan Tamils from the 1980s, Afghans, Rohingya, and millions of internally displaced persons and internal migrants alongside them. The scale is significant. Equally significant is the legal framework—or rather, the absence of one.

The Legislative Architecture of Exclusion: Foreigners Act, CAA, and NRC

Start with what is absent. India has never ratified the 1951 Refugee Convention or its 1967 Protocol. There is no domestic refugee law. The legal position of refugees was governed, for most of the period under analysis, by the Foreigners Act of 1946 — a colonial-era statute enacted by the Imperial Legislative Assembly, designed to give the state powers over foreign nationals. It defined a foreigner simply as someone who is not an Indian citizen. It made no distinction between tourists, migrants, and people fleeing persecution. Under Section 3(2), the Central Government could detain and deport. The burden of proving citizenship fell on the individual. The Act was repealed only in 2025 by the Immigration and Foreigners Act — but for the six decades it governed refugee lives in India, its consequences for documentation, education, and access were severe.

What this means for education is concrete. A refugee whose legal status is indistinguishable from an undocumented tourist has no enforceable right to schooling, no guaranteed service access, no legal protection from deportation. India has, in practice, extended different degrees of hospitality to different groups — through UNHCR administrative arrangements and bilateral understandings — but the variation this produces is itself the problem (Brinham & Johar, 2024). Tibetans have Registration Certificates, a Yellow Book for travel, reserved university seats, government-built schools. Rohingya are treated as illegal immigrants. Sri Lankan Tamils in Tamil Nadu camps occupy an uncomfortable middle ground. This differentiation is not based on any assessment of relative suffering. It is politics, strategic calculation, and the absence of any rights framework.

The Citizenship Amendment Act of 2019 changed the landscape in a specific and consequential way. The CAA amended the 1955 Citizenship Act to offer an accelerated citizenship pathway to undocumented migrants from Hindu, Sikh, Buddhist, Jain, Parsi, and Christian communities from Afghanistan, Bangladesh, and Pakistan — those who entered before December 2014. It was, explicitly, the first time religion appeared as a formal criterion in Indian citizenship law. The exclusion of Muslims — including Rohingya who fled genocide, Sri Lankan Tamils who do not qualify on other grounds — drew immediate criticism from the UN, Amnesty International, and multiple Special Rapporteurs. Article 14 of the Constitution guarantees equality; the CAA's critics argued it violated that guarantee (Government of India, 1949; USCIRF, 2020). The Supreme Court has heard challenges. Implementation rules were notified in March 2024.

For a paper concerned with AI-enabled education and displacement, the CAA matters for a specific reason. It establishes, for the first time in Indian legal history, that the state's willingness to extend protection and pathways to citizenship is organised by religious identity. When AI systems operating in educational governance contexts inherit the documentation infrastructure of this legal regime — when platform access requires Aadhaar, when Aadhaar requires stable documentation, when documentation reflects the stratified protections of the CAA — the algorithmic system reproduces the discrimination that the legislative framework has codified. The AI is not neutral with respect to the CAA. It inherits it.

The CAA must also be read alongside the National Register of Citizens (NRC), the parallel project to document all genuine Indian citizens. The Assam NRC — monitored by the Supreme Court and finalised in 2019 — excluded nearly 1.9 million people from its final list, many of them from marginalised communities including ethnic Bengali Hindus, women who had married across administrative boundaries, and members of the Tea tribes who lacked the specific documentary proof required (Hari & Nagpal, 2022). The consequences for those excluded are severe: inability to access food rations, bank accounts, employment, and education. Scholars have noted that UNICEF data shows only 52% of births are registered in India, meaning that the documentary burden placed upon citizens by the NRC is one that a substantial portion of the population — including many who are unambiguously Indian — cannot easily meet (Hari & Nagpal, 2022). For displaced, mobile, and poor populations, this documentation burden is not a bureaucratic inconvenience; it is the mechanism through which exclusion from public life, including education, is operationalised.

Educational access for refugees has consequently depended heavily upon community-led institutions and civil society interventions rather than systematic inclusion within national education systems. Tibetan refugees provide the most extensively documented example, having established an impressive network of schools under the aegis of the Central Tibetan Administration with support from the Government of India and international donors (Mishra, 2014; Mishra, 2022). Other refugee groups have experienced more precarious access — Sri Lankan Tamils in camps in Tamil Nadu, Afghan refugees in urban settlements, and Rohingya refugees facing particular marginalisation given India's lack of formal recognition of their status.

Internal Displacement, Migration, and the Right to Education Act

Numbers matter here. The Internal Displacement Monitoring Centre put India's internally displaced population at approximately 6 million in 2022 — and most scholars regard that as a substantial undercount. These are not refugees in the formal sense. They are Indian citizens displaced by dam construction, mining, conflict, floods, cyclones. Their children's schools shift with their parents' movements. Their educational records are spread across multiple states. They hold Indian citizenship — and yet the documentation requirements of Indian educational systems exclude them as effectively as any border.

The scale matters. India's internally displaced population was estimated at approximately 6 million in 2022 — and most scholars consider that a significant undercount. These are not refugees in the formal sense. They are Indian citizens displaced by dams, mines, conflict, floods, cyclones. Their children move with them. School records exist in multiple states, or nowhere. Documentation needed to enrol is often held by a different state authority than the one the family now lives under. The RTE Act of 2009 — which made free elementary education a fundamental right and placed a specific duty on local authorities to enrol migrant children under Section 9(k) — was supposed to change this. In practice, as the UNESCO GEM data shows, 80% of migrant children across seven Indian cities lacked access to education near worksites. The law and the reality remained far apart (UNESCO GEM, 2019; Chandrasekhar & Bhattacharya, 2018).

The distance between the RTE Act's provisions and their implementation for migrant children is well-documented. Local authorities frequently do not know how many migrant children are in their jurisdiction, are not familiar with the relevant provisions, and continue to require proof of residence for enrolment even where that requirement has technically been waived (Chandrasekhar & Bhattacharya, 2018). None of this is addressed by the arrival of AI-enabled educational platforms. If anything, it is compounded.

This is the terrain into which AI-enabled education is being introduced. The NEP 2020 acknowledges disadvantaged groups including migrants and commits to their inclusion. What it does not specify is what digital education means for children without Aadhaar, without stable addresses, without continuous school records. The emphasis on technology as the vehicle for inclusion risks encoding, into the foundations of those systems, precisely the structural conditions that produce exclusion in the first place.

Digital India and the Quiet Spread of AI

India's digital infrastructure expansion has been dramatic. Over 1.3 billion Aadhaar registrations. Digital payment systems now standard. Online welfare delivery normalised. The NEP 2020 makes technology-enabled learning and data-driven monitoring central to educational transformation (Government of India, 2020). The scale is real, and some of the reach is genuine.

What is striking, though, is the texture of how this AI revolution is actually arriving in India. A Times of India investigation published in February 2026 documented what it called 'AI's quiet spread beyond metros' — rural women doing data-labelling work from their homes in Jharkhand, farmers in Madhya Pradesh using AI-enabled pest detection apps, a Bengali farmer using an AI-based IoT farm lab, a village schoolboy in West Bengal using an AI tool to draft official documents and plans (Times of India, February 2026d). The story is, in one reading, inspiring. In another, it is revealing: the populations benefiting from this 'quiet spread' are generally those with fixed locations, some documentation, and enough stable infrastructure to engage with digital platforms. The displaced, the seasonally mobile, the undocumented — they are largely absent from this picture.

This digital expansion has significant implications for displaced populations. Aadhaar enrolment requires documentation that many displaced persons lack; biometric authentication can fail for elderly persons, manual labourers, or those with disabilities affecting fingerprints; and the assumption of fixed residential addresses underlying many digital systems conflicts with the mobility that defines displacement. Research has documented how Aadhaar-enabled welfare systems have produced exclusion errors — cases where entitled beneficiaries are denied services due to authentication failures, data mismatches, or documentation gaps (Khera, 2019; Panigrahi, 2021). When such systems extend to education, similar exclusion dynamics may affect displaced learners.

Critical Review: AI in Education and The Displacement Blind Spot

The scholarship on AI in education has grown fast over the past decade. It is not short of intelligence or sophistication. What it has consistently lacked is any serious engagement with displacement and mobility as conditions that shape large numbers of actual learners. The gap is not incidental. It reflects assumptions built into the research itself — assumptions about who the learner is, where they live, what continuity they have.

Dominant Narratives and Their Limits

The dominant narrative goes roughly as follows. AI in education can personalise instruction, provide immediate feedback, identify struggling students early, and reduce the burden on teachers (UNESCO Institute for Lifelong Learning, 2022). These are real possibilities. Adaptive platforms can do things that a single overworked teacher in a large classroom cannot. The claims are not dishonest. What they are is incomplete.

The incompleteness becomes visible when you ask what assumptions the narrative depends on. Effective adaptive learning requires continuous data. The algorithm needs to build a model of the learner over time — which requires the learner to be present, consistently, across sessions, on a device, with a connection. It requires a stable learner identity that the system can track. It requires educational goals that remain relatively constant. For a child in a seasonal labour camp, or a newly arrived refugee, or an internally displaced family moving every few months, almost none of these conditions hold.

The discourse about AI as an educational democratiser is similarly visible in India's mainstream media. The Times of India's Parenting supplement recently ran a feature asking whether AI is becoming 'the third parent' — noting that children are increasingly turning to chatbots in times of emotional distress and academic need (Times of India, February 2026a). Experts quoted in that piece warn that teaching healthy engagement might be key, and flag the risks of emotional dependency and the widening gap between children for whom AI is an accessible supplement and those for whom it remains out of reach. This mainstream framing is instructive precisely because of what it takes for granted: the child in question has a smartphone, a data connection, emotional bandwidth to engage with a chatbot, and a stable home from which to do so. The displaced child — in a transit camp, a seasonal labour site, a cramped urban settlement without documentation — does not figure in this conversation at all.

Evidence from Algorithmic Bias Research

Empirical evidence on algorithmic bias in education has grown rapidly. Predictive models for student success produce racially biased outcomes — less accurate for minoritised students (Gándara et al., 2024). AI tools designed without attention to linguistic background reduce engagement when cultural contexts do not match algorithmic assumptions (Farahani & Ghasemi, 2024). These are not surprising findings. What makes the India case specific and urgent is caste.

For India, the caste dimension adds a layer of particular urgency. The research reported in the Times of India (February 2026b), drawn from work by researchers at IIT and partner institutions, found that when GPT-4o and similar models are asked to assign jobs to persons with different names, they consistently favour upper-caste names for knowledge-economy roles and push lower-caste names toward manual or service work. The researchers describe the model's tendency to promote dominant castes while consistently associating Dalits and Shudras with lower-status roles—a pattern that emerged even when models were prompted to avoid bias. The implications for AI-enabled educational systems that make recommendations about academic tracks, career pathways, or learning interventions are serious and underexplored.

The Displacement Literature

In contrast to the technology-focused scholarship, research on refugee education has long highlighted structural barriers that no technology alone can resolve. Dryden-Peterson's (2011) wide-ranging global review documented how refugees encounter interrupted schooling, linguistic exclusion, curriculum misalignment, certification gaps, and teacher shortages — barriers rooted in political economy and institutional design rather than information scarcity. Technological interventions addressing symptoms while leaving structural causes untouched risk producing what critics term 'solutionism' — the application of technical fixes to fundamentally political problems.

Research on internally displaced persons points to similar themes: educational disruption persists not because solutions are technologically unavailable but because institutional arrangements fail to accommodate mobility, because resources are insufficient, and because displaced populations lack political voice to demand better (IDMC, 2022). The challenge is to bring these literatures into productive dialogue. AI education scholarship offers technical sophistication but displacement blindness; refugee education scholarship offers structural awareness but limited engagement with algorithmic systems.

Emerging Practices: AI-Enabled Education for Displaced Populations

Systematic research on AI specifically designed for refugee or IDP educational contexts is still thin. What exists is a mix of policy frameworks, pilots, and programmatic experiments — useful, but not yet a settled evidence base. What the available material does suggest is that the technology is rarely the limiting factor. Governance, institutional embedding, and sensitivity to context matter more than the sophistication of the tool itself.

Global Frameworks

UNHCR's Refugee Connected Education Challenge represents perhaps the most developed framework in this space. Its core insight is worth holding onto: technology is not a substitute for formal education. It is, at best, a complement — and only when three things are in place: quality, accredited content; capacity among both educators and learners; and reliable connectivity and infrastructure (UNHCR, 2019). UNESCO's comparative work adds that what distinguishes effective from ineffective technology-based interventions in displacement contexts is cultural responsiveness, linguistic inclusivity, and attention to learners' actual social circumstances (UNESCO Institute for Lifelong Learning, 2022). None of this is surprising. All of it is routinely ignored in practice.

Emerging Research Evidence

What limited evidence exists on AI-supported learning in refugee settings suggests cautious optimism under specific conditions. When AI tools are integrated into human-facilitated learning environments, with community-oriented pedagogies rather than substituting for them, engagement and psychosocial wellbeing can improve (ReadyAI, 2023). The word 'integrated' is doing a lot of work in that sentence. It means the tool is in a context — a relational, culturally embedded context. Strip that context out and the results deteriorate.

The 'unplugged' approaches that organisations like ReadyAI have developed are revealing in what they acknowledge: the most sophisticated AI tools remain beyond reach for many learners in displacement contexts. Teaching AI concepts without digital infrastructure at least ensures children are not simply excluded. It also — though this is rarely stated explicitly — acknowledges that understanding how AI works may matter as much as having it work for you.

The Indian Context

In India, there is almost no published research specifically on AI-enabled education for refugees or IDPs. The broader landscape gives us the relevant context. The NEP 2020 emphasises AI literacy and technology-mediated delivery. DIKSHA, SWAYAM, and the National Digital Education Architecture are the vehicles. The assumption throughout is that digital infrastructure is becoming available and that barriers to access are being progressively reduced. That assumption may be accurate for settled, documented, urban and peri-urban populations. For those who move, who lack documentation, who live in areas without stable connectivity, it does not hold.

The Aadhaar experience is instructive here. The system was built to streamline welfare delivery and reduce duplication. It has done this in some domains. It has also produced a well-documented set of exclusion errors — entitled beneficiaries denied food rations because biometric authentication failed, pensions blocked because data did not match, healthcare inaccessible because the number could not be verified. These are not hypothetical risks. They have been documented, litigated, and partially acknowledged by the Supreme Court. When education platforms follow the same logic, the same exclusions follow.

Internal Displacement, Migration, and The Challenges of Mobility

Internal displacement and seasonal migration receive far less attention than refugee flows in policy and research — despite affecting larger numbers of people in India. These are not marginal populations. In Bihar, Odisha, Chhattisgarh, and Jharkhand, seasonal migration is a central feature of working-class life. The children of migrant families are among the most educationally vulnerable in the country. Their situation is shaped by mobility, not by any single dramatic rupture — and that makes them harder to see and easier to ignore.

Educational Disruption in Mobile Contexts

Children from displaced and migrant families encounter multiple barriers to educational continuity. Frequent movement disrupts attendance and prevents sustained engagement with curricula designed for sedentary learners. Documentation requirements for school enrolment may be impossible to satisfy when families lack permanent addresses or recognised identity papers. Linguistic differences between states of origin and destination compound learning difficulties, particularly for children moving across India's linguistic regions.

The research on seasonal migration patterns in India documents something straightforward: the educational calendar and the migration calendar do not match. Brick kiln work, sugarcane cutting, construction labour — these move families during the school term. Children go with parents, as carers for younger siblings, as additional earners, or simply because there is no alternative. Months of schooling are lost. The losses accumulate into permanent disadvantage. An adaptive learning algorithm trained on attendance data encounters these children's records and reads structural displacement as individual disengagement. It would be wrong — and the wrongness would have consequences.

Institutional Responses and Their Limitations

Effective programmatic responses to this situation share a common logic: they adapt to the child's mobility rather than requiring the child to overcome it. Bridge schools offer condensed instruction during migration periods. Seasonal hostels let children stay behind when parents leave. Mobile teachers travel with migrant communities. Worksite schools follow families to brick kilns and construction sites. These approaches work. What makes them work is relational — teachers who know individual children, communities that trust the institution, continuity built through human relationships rather than through data systems.

The implication for AI is direct. The mechanisms that make education work for mobile children are precisely the mechanisms that AI cannot replicate. An adaptive learning platform cannot know a child the way a mobile teacher who has travelled with their family knows them. It cannot build community trust. It cannot adjust to circumstances it has not been programmed to anticipate. This is not a temporary limitation awaiting a technical solution. It reflects what education for mobile populations actually requires.

Digital Education and the Reproduction of Exclusion

Digital and AI-enabled education is frequently proposed as the solution that transcends geography — available anywhere, requiring no local presence, scalable without limit. The pitch is seductive. The evidence for it, in displacement contexts, is limited. What the evidence actually shows is that when the underlying structural constraints — documentation gaps, connectivity gaps, mobility, poverty — go unaddressed, digital systems reproduce existing exclusions efficiently rather than resolving them.

The displaced child in this scenario is not lazy. Not disengaged. Not constitutionally at risk. But an algorithm trained on attendance data, progress metrics, and engagement patterns will not know the difference between a child who has been out of school for three months because of seasonal migration and one who has dropped out. The recommendation it generates will be wrong. And in the logic of algorithmic systems, being wrong consistently, at scale, is how inequality is reproduced in a new technical form.

AI, Governance, and The Politics of Educational Decision-Making

When AI enters educational governance, something shifts. Not just in how decisions are made — in who makes them, and with what accountability. A teacher who places a child in a remedial stream is visible, reachable, contestable. An algorithm that makes the same recommendation is opaque, technically legitimate, and hard to challenge. For displaced learners, whose families are often unfamiliar with educational bureaucracies, who may fear authorities, who lack the linguistic resources to navigate formal systems — this shift in decision-making is not neutral. It reduces already limited recourse.

Algorithmic Authority and the Displacement of Judgement

Teachers, counsellors, and school administrators make decisions about children based on contextual knowledge built over time. They know when a student's poor performance reflects limited ability and when it reflects a crisis at home, a recent traumatic experience, or a documentation problem that has disrupted attendance. That contextual knowledge is relational. It comes from relationships. When algorithmic systems make or strongly influence these decisions, the contextual knowledge is stripped out and replaced with pattern-matching on available data.

The consequences for displaced learners are specific. Their circumstances routinely produce precisely the patterns that algorithms flag as risk: absences, gaps in records, underperformance on standardised assessments, inconsistent engagement. A teacher who knows the child knows what these patterns mean. An algorithm does not. The result is that displaced children may be systematically misread at exactly the moments when getting the assessment right matters most.

Digital Identity and Access

Aadhaar offers the clearest illustration India has of digital identity infrastructure in practice — its possibilities and its failures. The system has extended coverage widely. It has also produced exclusion. The Supreme Court's 2018 ruling acknowledged this, holding that Aadhaar cannot be mandatory for essential services precisely because authentication failures were denying entitled citizens access to food, healthcare, and pensions. The exclusions were not bugs. They were predictable consequences of a system that assumed stable documentation, stable biometrics, and stable addresses. Educational platforms built on similar infrastructure will produce similar outcomes.

For displaced learners, documentation gaps create cascading barriers. Without recognised identity documents, obtaining Aadhaar may be impossible; without Aadhaar, accessing digitally mediated services becomes difficult; without access to digital educational platforms, learning opportunities narrow. AI systems built upon digital identity infrastructure may thus inherit exclusion mechanisms operating upstream of the education system itself.

Transparency, Accountability, and Redress

Accountability is the central question. For displaced populations — legally precarious, often fearful of state institutions, linguistically marginalised — the ability to contest algorithmic decisions is already constrained. Proprietary systems may be opaque even to the institutions deploying them. Without deliberate design for contestability and redress, AI in education becomes governance without recourse for the very populations most vulnerable to its errors.

Education, Identity, and Diversity: Insights from Tibetan Refugees in India

I want to be careful here not to let this section become merely illustrative — a case study that confirms what the theoretical framework has already established. The Tibetan refugee community in India is genuinely complex, and that complexity has taught me things I did not expect to learn. What follows draws upon ethnographic research conducted over an extended period, documented in Tibetan Refugees in India: Education, Culture, and Growing Up in Exile (Mishra, 2014) and in subsequent published work (Mishra, 2022), as well as ongoing fieldwork and reflection that has continued to refine my understanding.

I am, of course, not the first scholar to study this community. Girija Saklani's (1984) foundational sociological study of Tibetan refugees — grounded in fieldwork in Dharamshala, Delhi, and Dehradun — remains an essential reference, documenting the remarkable social and economic adaptation of a community that had arrived with almost nothing. Saklani captured something important: the relationship between continuity and change that defines exile community formation. Where I would supplement her analysis is in attending to the internal differentiation that has deepened over subsequent decades, and to the educational implications of that differentiation. Dibyesh Anand's postcolonial scholarship on Tibetan diaspora identity offers another essential perspective—his critique of essentialist constructions of 'Tibetanness' and his attention to how the diaspora has invested in particular representations of identity for strategic purposes (Anand, 2000; 2003) provide the political context within which educational institutions operate. The Tibetan school system is not simply educating children; it is constructing a national subject in exile. That is a fundamentally different project from what most educational AI systems are designed to support.

Migration Histories and Educational Trajectories

Among the most significant distinctions within the Tibetan refugee population lies between those born in India to refugee parents or grandparents and those who arrived from Tibet — often as unaccompanied minors. This distinction between what I have called settlement-born Tibetans and newcomers shapes educational experiences profoundly, and in ways that no standardised learner profile could capture.

Individuals born in Tibet typically experienced early childhood socialisation within Tibetan cultural and linguistic environments, followed by abrupt disruption through migration. Many arrived having attended Chinese-medium schools where Tibetan language instruction was limited or absent. Their educational trajectories in India were marked by discontinuity, adjustment challenges, and the emotional weight of separation from family. Some possessed strong foundations in Mandarin Chinese but required intensive support in English and Hindi; others arrived with limited formal schooling.

By contrast, Tibetans born in India grew up within institutional settings shaped by six decades of exile community-building. They developed familiarity with Indian languages and social norms from early childhood. Their educational trajectories, while still shaped by exile conditions, followed more predictable patterns. Yet they too faced particular challenges: accusations from newcomers of being insufficiently Tibetan, questions about cultural authenticity, and complex negotiations between Indian, Tibetan, and increasingly global identities. Neither group fits the profile of a standardised 'refugee learner.'

Institutional Cultures and Educational Goals

Schooling institutions further shaped these differences. Tibetan-run schools — particularly the Tibetan Children's Village system and Central Tibetan Schools Administration institutions — were designed to serve both educational and cultural-political objectives. These schools provided instruction that was often bilingual or Tibetan-medium in early years, with curricula emphasising Tibetan history, religion, and collective identity alongside standard academic subjects. Education in these settings was framed explicitly as responsibility toward cultural preservation and the broader political project of exile — maintaining Tibetan identity so that future return to Tibet would find a community intact rather than assimilated.

In contrast, Tibetan students educated in Indian convent schools or government schools encountered different institutional cultures. These schools prioritised English or Hindi as the medium of instruction and aligned with mainstream Indian curricula. Students in such settings often developed greater facility navigating Indian higher education institutions and labour markets, and tended to articulate broader career aspirations, including professional roles within Indian society and transnational spaces.

What strikes me, looking back at this material, is how inadequate any algorithmic approach to 'personalised learning' would be in this context. An adaptive learning system that adjusted content difficulty based on prior performance data would be working with fragments — incomplete records, inconsistent assessment, educational histories that crossed national and linguistic boundaries. It would have no way of knowing whether a student's apparent weakness in English reflected a cognitive gap or simply the fact that they had spent their first twelve years in a Chinese-medium school in Lhasa.

Language, Identity, and Belonging

Language operates as a central site of tension in Tibetan refugee education. The Tibetan language — in its literary, spoken, and regional varieties — carries profound significance as a marker of identity, vehicle of religious practice, and connection to homeland. Yet educational and economic success in India frequently requires English and Hindi, while younger generations increasingly gravitate toward global English as a medium of aspiration.

My research documented how language competencies shaped social positioning within the refugee community. Newcomers speaking Tibetan with accents or vocabulary influenced by Chinese were sometimes stigmatised as culturally contaminated. Settlement-born youth who struggled with literary Tibetan faced questions about their authenticity. English proficiency opened doors to employment but also created distance from older community members. These linguistic dynamics intersected with generational differences, regional origins, and social class to produce complex hierarchies of belonging that no algorithm would be equipped to navigate.

My own fieldwork documented these dynamics in considerable depth (Mishra, 2014). For newly arrived young Tibetans — separated from families left behind in Tibet, navigating an unfamiliar institutional landscape in India — the pursuit of educational credentials becomes entangled with a quest to recover a sense of self that has been profoundly disrupted. The educational aspiration is real and often intense; so is the structural precarity surrounding it. What I observed repeatedly was that the fragmentation visible in a student's academic record — gaps, inconsistencies, apparent underperformance — was not evidence of limited ability but of the extreme conditions from which they were trying to rebuild a life. An AI adaptive learning system calibrated to progress metrics and engagement data would encounter these learners at their most vulnerable moment and interpret their fragmentation as underperformance. It would be wrong, in ways that matter enormously for the child in question.

What the Tibetan Case Reveals

The goals of education in this community extend far beyond individual skills acquisition. Education serves collective purposes: maintaining language that might otherwise be lost, transmitting historical memory to generations who have never seen Tibet, preparing potential leaders for uncertain political futures. AI systems oriented toward individualised learning outcomes may fail to support — or may actively undermine — these collective educational projects. This is not a romantic or traditionalist point. It is an empirical observation about what communities actually want from education, and what they will resist if education does not provide it.

The parallels with other displacement contexts are worth noting. The Ukrainian children described in the Times of India op-ed — growing up without heat and stable schooling, their parents told they will never forget — are not simply behind on a curriculum. They are experiencing an interruption of collective life that education must eventually repair, not just an individual skills gap that adaptive software can fill (Times of India, February 2026c). Understanding that difference requires the kind of contextual, historically informed, relational knowledge that the best teachers and community workers bring to their work. It cannot be automated.

Implications for AI Design and Educational Governance

Against Standardisation

AI systems in education generally do what they are designed to do: standardise. They apply uniform data categories, consistent assessment rubrics, normalised pathways. For most learners, this is manageable. For displaced learners — who have interrupted schooling histories, multilingual competencies, culturally specific educational goals, and migration trajectories that cross administrative boundaries — standardisation does not fit. The variation that standardised systems treat as noise is, in fact, the signal.

The argument is not against AI. It is for a different kind of AI design — one that accommodates heterogeneity rather than minimising it. This means flexible assessment that can recognise competence expressed in multiple forms. It means adaptive systems that adjust not just difficulty but modality, language, and content. It means credentialing that values diverse pathways rather than enforcing a single standard. None of this is technically impossible. All of it requires deliberate design choices that current systems do not make.

Data Justice and Representation

Data shapes what algorithms learn, and displaced populations generate less data — and less legible data — than settled ones. This underrepresentation is not random. It reflects the same marginalisation that produces educational disadvantage in the first place. An AI system trained on data that systematically excludes displaced learners will perform worse for them. Addressing this is ethically complex: generating better data raises its own concerns about surveillance, consent, and the potential misuse of information about vulnerable populations. There is no clean technical fix.

Human Oversight and Professional Judgement

Human oversight in educational decision-making is not optional for displaced populations — it is a condition of doing the work responsibly. AI tools can usefully support educators: identifying learning gaps, flagging students who may need support, suggesting resources. But the consequential decisions — placement, progression, certification — cannot be safely delegated to algorithmic systems for learners whose circumstances require interpretation that standard data cannot capture. The educator who knows the child must retain that authority.

Community Participation and Accountability

In my fieldwork with Tibetan refugees, one thing became clear early: the community had educational goals that no external designer would have predicted. They were not primarily concerned with optimising individual outcomes for Indian labour market entry. They were concerned with cultural survival — with maintaining a language, transmitting a historical memory, producing people who could carry a political project forward under conditions of exile. AI systems designed around individualised learning outcomes would have missed this entirely. Governance of AI in education for displaced communities must include those communities.

Human Judgement, Refugee Status Determination, and The Limits of Automation

I want to dwell here on something that has shaped my thinking in ways that are difficult to fully systematise. Between 2001 and 2003 — first as an intern in UNHCR's Community Services and Protection Unit in New Delhi, and then as a Consultant and Social Worker at the Socio-Legal Information Centre (SLIC), an implementing partner of UNHCR — I worked directly with refugee communities on protection and socio-legal matters. This was simultaneous with my M.Phil research on Afghan and Tibetan refugee children. The two things were not separate: what I encountered in the SLIC office during the week shaped what I was trying to understand through my research. That experience has never left me, and it speaks directly to the question of what automation can and cannot do in high-stakes decisions involving displaced populations.

RSD as Interpretive Practice

Refugee Status Determination is, at its core, an interpretive act. An adjudicator listens to a narrative — often fragmented, non-linear, shaped by trauma, fear, and cultural norms about what can be said to a stranger in a formal setting — and makes a judgement about whether that person faces a well-founded fear of persecution. There is no algorithmic substitute for this. What looks like inconsistency to a pattern-matching system is often entirely explicable to someone with country knowledge, cultural competency, and the capacity to attend to a particular human being in front of them.

This process resists reduction to algorithmic decision-making. Asylum narratives may be fragmented, non-linear, or incomplete — not because claimants are fabricating but because trauma affects memory, because cultural norms shape self-presentation, and because fear affects disclosure. What looks like inconsistency to a pattern-matching system may be entirely explicable to a trained interviewer with country knowledge and attentiveness to the specific person sitting across the table. The stakes of error — returning someone to persecution — demand accountability that algorithmic systems cannot provide.

Recent policy debates have explored AI applications in asylum processing and identity verification. Proponents argue that automation could improve efficiency, consistency, and speed. Critics counter that algorithmic systems risk entrenching bias, excluding populations poorly represented in training data, and eroding the individualised assessment that international law requires. I count myself firmly among the critics — not merely on abstract principle but from having spent over a year at SLIC watching what refugee protection work actually requires: patience, contextual knowledge, the ability to hold a person's fragmented story with care and interpret it accurately. Those qualities cannot be automated.

Parallels with Educational Assessment

The parallels with educational assessment run directly. A displaced student's academic record may be fragmented, inconsistent, lacking documentation — for the same reasons an asylum narrative may be fragmented: not because the person is deficient, but because the institutions that normally generate evidence of competence were disrupted by exactly the forces that caused their displacement. Reading those gaps as evidence of low ability is wrong in precisely the same way that reading a non-linear asylum narrative as evidence of fabrication is wrong.

Automated assessment systems make exactly this error. They flag the absences, the inconsistencies, the gaps — and generate recommendations based on surface patterns rather than underlying realities. The capable student is misclassified. The intervention recommended is wrong. The opportunity is closed. These are not hypothetical errors. They are the predictable consequences of applying pattern-recognition to populations whose patterns have been shaped by exceptional circumstances that the training data does not contain.

The Enduring Importance of Human Agency

Both domains — asylum processing and educational assessment — point toward the same conclusion about the appropriate role of automation. AI can support human decision-making. It can process information, identify patterns, flag cases that need attention. What it cannot do is replace the judgement, accountability, and ethical reasoning that consequential decisions require. This is not a romantic defence of human decision-making, which has its own well-documented biases. It is a recognition that algorithmic systems and human judgement have different failure modes — and that for populations whose situations require contextual interpretation, the failure modes of algorithmic systems are more dangerous.

Policy Framework: Towards Equitable AI-Enabled Education

The policy implications of this analysis are concrete. Current governance frameworks for AI in education — at national and international levels — treat displacement as peripheral. Mobile and displaced learners appear, if at all, as edge cases requiring special provisions. The argument of this paper is that they should be treated as a design requirement: as populations whose inclusion must be built into AI systems from the outset, not retrofitted afterwards.

Recognition of Displacement as Structural Condition

Recognition matters first. Policy frameworks should explicitly name displacement — external and internal — as a structural condition affecting significant learner populations in India and globally. This has practical implications: educational technology standards should include mobility requirements; impact assessments should evaluate effects on displaced populations before systems are deployed; funding should support AI applications designed for displacement contexts rather than simply adapted from systems built for settled ones. For India, this means the NEP 2020 implementation guidelines must answer a question they currently avoid: what does digital education mean for children without Aadhaar, without fixed addresses, without continuous schooling records?

Flexibility in Credentialing and Assessment

Credentialing flexibility is essential. The rigid progression requirements embedded in most educational AI systems create barriers that such systems enforce more efficiently than human gatekeepers ever could. Displaced learners with interrupted schooling histories, credentials from unrecognised institutions, or non-linear educational trajectories cannot navigate these requirements. Recognition of prior learning, modular credentialing, and alternative assessment mechanisms should be design requirements, not afterthoughts.

Multilingual and Culturally Responsive Design

Linguistic and cultural responsiveness must be built in from the start, not layered on after deployment. For displaced populations in India — who may speak any of dozens of languages, who may come from educational traditions that differ from Indian mainstream norms, whose educational goals may be shaped by cultural and political projects that adaptive systems are not designed to recognise — translation of interfaces is the minimum. What is needed is adaptation of pedagogical approaches, assessment instruments, and content. For India specifically, this includes addressing caste bias in the language models that underpin educational AI — the research evidence now makes clear that this bias exists and is systematic. It cannot wait.

Safeguards Against Exclusion

Safeguards against exclusion are non-negotiable. Human override mechanisms. No mandatory digital identity requirements for educational access. Data protection standards that prevent the surveillance of vulnerable populations. Regular audits that identify disparate impacts on displaced and mobile learners. These should be requirements, not recommendations.

Participatory Governance

Participation by affected communities is not a consultation exercise. It is a governance requirement. The Tibetan case I have documented over decades illustrates why: communities whose educational goals are shaped by cultural survival, collective identity, and political aspiration will resist AI systems that reduce education to individualised skills acquisition — and rightly so. Meaningful participation means representation in standards development, involvement in system design, and access to redress mechanisms that work for people constrained by legal status, linguistic marginalisation, or economic precarity.

Preservation of Human Judgement

Human judgement must remain central to high-stakes educational decisions. AI systems can inform — they can process data, flag patterns, suggest resources. They should not have final authority over placement, progression, certification, or opportunity for learners whose circumstances require the kind of contextual interpretation that data systems cannot perform. This is especially true for displaced learners. Their situations demand educators capable of understanding what the data cannot show.

Conclusion: Educational Justice in Mobile Futures

I began this paper with three newspaper stories, and I want to return to them in closing. The story about AI as third parent, the story about Ukrainian children who will never forget their displacement, and the story about caste bias in language models — these three are not separate phenomena. They are facets of the same problem: we are building AI systems for education in a world of profound mobility, inequality, and diversity, while imagining a world of settled, documented, homogeneous learners.

The conclusions I draw are not pessimistic ones. I have seen, in my fieldwork among Tibetan refugees, what education can accomplish in conditions of profound adversity. I have seen communities build schools, preserve languages, transmit historical memory across generations, and maintain collective identity through deliberate institutional effort. Technology did not do this — people did, with vision, commitment, and an understanding of what was at stake. The question is whether AI, thoughtfully governed, can support rather than undermine this kind of work.

The path forward requires not abandoning technology but governing it wisely — ensuring that AI serves educational justice rather than deepening the marginalisation of those already most excluded. For India, where refugees, migrants, and internally displaced persons navigate complex educational landscapes amid rapid digital expansion, aligning AI-enabled education with principles of equity and inclusion is both a policy imperative and moral necessity.

Four specific challenges deserve priority attention as this agenda moves forward. First, the caste bias documented in current large language models must be addressed before those models are deployed in Indian educational settings — this is a concrete, tractable problem that researchers and developers have now clearly identified. Second, the digital identity requirements embedded in educational platforms must be redesigned to accommodate learners without stable documentation or fixed addresses. Third, the relational and community dimensions of education for displaced populations must be recognised as features to be supported by AI, not functions to be replaced by it. And fourth, displaced communities — including the Tibetan community in India, internal migrants, and others — must have meaningful participation in the governance of systems that will shape their children's educational futures.

The choices made now about how to design, deploy, and govern educational AI will shape the life chances of displaced children and youth for generations. Those children — including the Ukrainian children whose story appeared in an Indian newspaper on the fourth anniversary of their displacement — are not edge cases to be handled by a special module. They are the test of whether our commitment to educational justice is real.

References

Anand, D. (2000). (Re)Imagining nationalism: Identity and representation in the Tibetan diaspora of South Asia. Contemporary South Asia, 9(3), 271–287.

Anand, D. (2003). A contemporary story of diaspora: The Tibetan version. Diaspora: A Journal of Transnational Studies, 12(3), 211–229.

Baker, R.S., & Hawn, A. (2021). Algorithmic bias in education. International Journal of Artificial Intelligence in Education, 32, 1052–1092.

Banerjee, P. (Ed.). (2005). Internal displacement in South Asia: The relevance of the UN's

Guiding Principles. Sage Publications.

Banerjee, P. (2010). Borders, histories, existences: Gender and beyond. Sage Publications.

Benjamin, R. (2019). Race after technology: Abolitionist tools for the new Jim Code. Polity Press.

Bourdieu, P. (1986). The forms of capital. In J.G. Richardson (Ed.), Handbook of theory and research for the sociology of education (pp. 241–258). Greenwood Press.

Bourdieu, P., & Passeron, J.C. (1990). Reproduction in education, society and culture (2nd ed.). Sage.

Brinham, N., & Johar, A. (2024). Refugee experiences of identity documents and digitisation in India and Myanmar. Journal of Refugee Studies, 37(1), 45–68.

Brookings Institution. (2020). India's National Education Policy 2020: A reformist step forward? https://www.brookings.edu/blog/education-plus-development/2020/08/12/indias-national-education-policy-2020/

Chandrasekhar, S., & Bhattacharya, L. (2018). Education of children from migrant rural households in India: Moving towards a coherent policy framework (Background paper GEM Report 2019). UNESCO.

Citizenship (Amendment) Act, 2019, No. 47, Acts of Parliament, 2019 (India). https://egazette.nic.in/WriteReadData/2019/214646.pdf

Citizenship Act, 1955, No. 57, Acts of Parliament, 1955 (India) (as amended 2019).

Foreigners Act, 1946, No. 31, Acts of Parliament, 1946 (India). [Superseded by the Immigration and Foreigners Act, 2025.]

Dryden-Peterson, S. (2011). Refugee education: A global review. UNHCR.

Erel, U. (2010). Migrating cultural capital: Bourdieu in migration studies. Sociology, 44(4), 642–660.

Farahani, M., & Ghasemi, S. (2024). Algorithmic bias in educational systems: Examining the impact of AI-driven decision making in modern education. World Journal of Advanced Research and Reviews, 25(1), 253–269.

Gándara, D., Anahideh, H., Ison, M.P., & Picchiarini, L. (2024). Inside the black box: Detecting and mitigating algorithmic bias across racialized groups in college student-success prediction. AERA Open, 10, 1–20.

Global Partnership for Education. (2024). Education for refugees. https://www.globalpartnership.org/focus-areas/refugees-and-displaced-populations

Government of India. (1949). The Constitution of India. https://legislative.gov.in/constitution-of-india

Government of India. (2020). National Education Policy 2020. Ministry of Education.

Hari, A., & Nagpal, S. (2022). The National Register of Citizens (NRC) in India and the potential for statelessness in situ: A cautionary tale from Assam. Contemporary South Asia, 30(2), 156–172.

Internal Displacement Monitoring Centre. (2022). Barriers to education for internally displaced children. IDMC.

Khera, R. (2019). Dissent on Aadhaar: Big data meets big brother. Orient BlackSwan.

Knox, J. (2020). Artificial intelligence and education in China. Learning, Media and Technology, 45(3), 298–311. https://doi.org/10.1080/17439884.2020.1754236

Malkki, L. (1995). Refugees and exile: From 'refugee studies' to the national order of things. Annual Review of Anthropology, 24, 495–523.

McConvey, K., & Guha, S. (2024). Algorithmic accountability in education: Challenges and opportunities. Journal of Learning Analytics, 11(1), 45–62.

Mishra, M. (2014). Tibetan refugees in India: Education, culture, and growing up in exile. Orient BlackSwan.

Mishra, M. (2022). Education of Tibetan refugees: Sowing future seeds of Tibet. In S. I. Rajan (Ed.), The Routledge handbook of refugees in India (pp. 565–583). Routledge.

Noble, S.U. (2018). Algorithms of oppression: How search engines reinforce racism. NYU Press.

Panigrahi, S. (2021). Marginalized Aadhaar: How the world's largest digital identification programme led to the exclusion of marginalised communities. Yoti Foundation. https://www.yoti.com/blog/yoti-fellowship-marginalised-aadhaar/

ReadyAI. (2023). We need to bridge the AI education gap for refugees. Medium. https://medium.com/readyai-org/we-need-to-bridge-the-ai-education-gap-for-refugees

Right of Children to Free and Compulsory Education Act, 2009, No. 35, Acts of Parliament, 2009 (India). https://legislative.gov.in/sites/default/files/A2009-35.pdf

Saklani, G. (1984). The uprooted Tibetans in India: A sociological study of continuity and change. Cosmo Publications.

Samaddar, R. (Ed.). (2003). Refugees and the state: Practices of asylum and care in India, 1947–2000. Sage Publications.

Samaddar, R. (2020). The postcolonial age of migration. Routledge.

Times of India. (2026a, February). How AI is becoming the third parent, and why that's scary. Times of India.

Times of India. (2026b, February). AI knows how caste works in India. Here's why that's a worry. Times of India.

Times of India. (2026c, February). 'Our kids growing up without heat & stable schooling, displaced from their homes...will never forget' [Op-ed by Oleksandr Polishchuk]. Times of India.

Times of India. (2026d, February). AI's quiet spread beyond metros. Times of India.

UNESCO Institute for Lifelong Learning. (2022). From radio to artificial intelligence: Education for displaced populations. UNESCO.

UNESCO Global Education Monitoring Report. (2019). Migration, displacement and education: Building bridges, not walls. UNESCO.

UNHCR. (2019). Refugee connected education challenge. https://www.unhcr.org/refugee-connected-education-challenge.html

United States Commission on International Religious Freedom. (2020). Factsheet on the Citizenship (Amendment) Act in India. USCIRF. https://www.uscirf.gov/sites/default/files/2020%20Factsheet%20-%20India%20CAA_0.pdf