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# Bridging the AI chasm: A strategic framework for generative AI in higher education

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**Abstract**
This article examines the reluctance of academic institutions in developing countries to embrace generative artificial intelligence (AI) through a critical lens. Technology adoption involves complex negotiations between acceptance and resistance, shaped by infrastructural constraints, digital literacy gaps, and post-colonial considerations that complicate straightforward implementation. Through a systematic literature review and conceptual analysis, we argue that strategic adoption of generative AI represents more than technological upgrading, it offers transformative potential to address entrenched educational inequalities and prepare graduates for global engagement. Resistance emerges not primarily from technophobia but from legitimate ethical concerns, digital divides, and cultural relevance issues. The study proposes a context-sensitive integration framework emphasizing human-centred design, localized competency building, and ethical governance. We contend that higher education policymakers and practitioners in developing countries should lead in establishing fair, culturally appropriate AI ecosystems aligned with local developmental priorities while pursuing global academic excellence.

**Keywords:** Acceptance of technology; Developing countries; Digital divide; Ethical governance; Generative artificial intelligence; Higher education integration framework

## 1. Introduction

The global proliferation of generative AI applications heralds a fourth industrial revolution in education, promising augmented personalized learning, innovative research methodologies, and administrative efficiency gains. However, implementation trajectories reveal stark geographical divergence, with developing nations demonstrating marked reluctance to integrate generative AI into higher education infrastructures. This resistance exists paradoxically alongside unprecedented global uptake of tools like ChatGPT, which reached 100 million users within two months, a pace dwarfing previous technological adoptions (World Economic Forum, 2024). The lag in systematic institutional integration in developing countries signals deeper structural issues, reflecting what United Nations discussions identify as a widening digital divide that risks excluding the world's poorest from technological dividends (United Nations, 2023).

This article examines resistance to generative AI in developing countries' higher education through a critical lens, arguing that such resistance often stems from legitimate structural, ethical, and pedagogical concerns rather than technological illiteracy. These concerns warrant serious engagement rather than dismissal. Our central thesis conceptualizes technological advances as presenting societies with a spectrum of positions between adoption and resistance, rather than a binary choice. Developing countries currently occupy various points along this continuum, with some institutions implementing restrictive policies while others pursue tentative integrative governance.

The research addresses several interconnected questions: What primarily drives hesitancy toward generative AI adoption in developing countries' higher education? How do these drivers differ from those in developed countries? How can equitable integration paradigms respond to legitimate concerns while harnessing AI's transformative potential? What methodological rigor supports claims about AI's educational contributions in developing contexts?

Recent UNESCO data indicates nearly 90% of academics globally use AI tools professionally, yet confidence remains uneven, with over half expressing uncertainty about effective pedagogical applications (UNESCO, 2025). In developing regions, this uncertainty is exacerbated by infrastructural limitations and resource constraints. Nevertheless, AI presents unprecedented opportunities for educational leapfrogging potentially addressing teacher shortages, personalizing instruction, and democratizing access to quality education, as noted at the 2023 World Bank conference. This paper argues that developing economies stand at a critical juncture where conscious, strategic utilization of generative AI can reposition higher education from maintaining power imbalances to enabling greater inclusive growth and global equity. This is summarized as illustrated in Table 1.

Table 1
*AI utilization comparison for regions*

| *Region* | *Institutional AI Policy Status* | *Main Determinants* | *Focus on investments* |
|---|---|---|---|
| Europe & North America | ~70% | Ethical management, academic robustness | Research facilities, faculty development |
| Latin America & Caribbean | ~45% | Access equality, cultural relevance | Basic infrastructure, student access |
| Asia-Pacific | Varies substantially (Singapore 70%+) | Economic competition, job displacement | National AI plans, industry cooperation |
| Sub-Saharan Africa | Under 30% | Infrastructure deficit, digital literacy | Fundamental connectivity, availability of devices |

## 2. Literature Review

### 2.1. Context of Introduction of AI in College and University Environments

Artificial intelligence integration into higher education has progressed unevenly worldwide, revealing major divisions that researchers term the digital knowledge gap. This is further subdivided by resource availability rather than pedagogical innovation. A UNESCO survey of 400 higher education institutions across 90 countries found that two-thirds have or are developing AI use guidance, though significant regional gaps persist in implementation capacity and confidence (UNESCO, 2025). In developing countries, this divide manifests as what Valentini and Blancas (2025) describe as "fragmented institutional responses" resulting in piecemeal AI implementations with decentralized strategies focusing more on plagiarism detection than comprehensive pedagogical transformation. The divide is quantifiable: while 63% of the global population was online in 2021, this figure drops to 27% in Least Developed Countries (United Nations, 2023).

Literature indicates developing countries face amplified versions of global challenges entailing ethical concerns about bias, threats to academic integrity, and questions about AI's role in knowledge production. They additionally confront context-specific constraints including inadequate digital infrastructure, limited device access, erratic electricity, and insufficient faculty readiness. Research from Türkiye illustrates this disparity: while university students exhibit positive attitudes toward AI, practical integration is hindered by structural limitations beyond individual readiness (Türk et al., 2025). These findings challenge simplistic stereotypes attributing resistance primarily to technophobia or cultural conservatism, pointing instead to material and structural limitations requiring targeted address.

### 2.2. Theoretical Justification and Framework for Technology Adoption and Resistance

Anticipating resistance to generative AI requires engagement with theoretical lenses on technology acceptance dynamics. The Technology Acceptance Model [TAM] historically dominated discussions, positing perceived utility and ease of use as primary adoption determinants (Jiang et al., 2024). However, newer integrative models combining TAM with Protection Motivation Theory [PMT] and Social Exchange Theory [SET] offer more nuanced explanations for concurrent acceptance and resistance in developing contexts (Shrivastava, 2025).

From this integrative perspective, resistance represents strategic response to perceived threats—privacy violations, cultural erosion, algorithmic bias, academic devaluation—rather than reflexive opposition. Emerging literature from developing countries emphasizes the neo-colonial dimensions of technology diffusion, arguing that technologies developed in Western contexts often embed particular social and epistemic assumptions that may marginalize or alienate indigenous knowledge systems (Couldry & Mejias, 2019; Mignolo, 2011).This literature suggests stakeholders in developing nations conduct sophisticated risk-benefit analyses weighing immediate educational impacts against long-term considerations of national sovereignty, cultural integrity, and economic development.

### 2.3. Specificity of Educational Technology Use in Developing Nations

Literature highlights several unique determinants shaping generative AI adoption in higher education institutions across developing countries. First, resource constraints and infrastructure gaps often lead institutions to prioritize foundational digital capacity before investing in advanced AI systems (Adam, 2019). Second, concerns about technological dependence and vendor lock-in intensify where local capacity to customize, govern, and maintain imported digital infrastructures remains limited (Couldry & Mejias, 2019). Third, growing awareness of AI's structural power asymmetries has prompted critique that most generative AI systems—developed primarily by corporations in North America and parts of Asia—may embed particular epistemological assumptions that risk marginalizing local and indigenous knowledge systems (Birhane, 2020; Mignolo, 2011).

Research also emphasizes AI's ambivalent potential in less developed regions: while potentially exacerbating social disparities through what the World Bank terms "digital Matthew effects" (disproportionately benefiting the wealthy), AI also offers unprecedented opportunities for educational leapfrogging (World Bank, 2023). The United Nations cautions about possible "winner-take-all" dynamics where dominant entities control the data economy, crowding out development options for less developed regions (United Nations, 2023). Studies from India and Uganda demonstrate AI's potential for addressing teacher shortages and personalizing instruction at scale, while South African research shows AI's capacity to extend expertise to underserved areas (Nguyen & LeBoeuf, 2023). This literature suggests developing nations face not binary choices but intricate negotiations between aspirational promise and practical constraints.

### 2.4. Regional Heterogeneity in AI Adoption Patterns

While developing countries share common challenges, significant regional and national variations necessitate differentiated analysis. Table 2 illustrates these variations, moving beyond a homogeneous "developing world" categorization (UNESCO 2025).

These regional differences manifest in distinctive adoption patterns:

(i). Infrastructure-first approaches in Sub-Saharan Africa prioritize basic connectivity before advanced AI integration.

(ii). Scale-oriented models in South Asia emphasize reaching large student populations with cost-effective solutions.

(iii). Quality enhancement strategies in Latin America focus on pedagogical transformation over technological adoption per se.

(iv). Economic competitiveness drivers in Southeast Asia link AI education directly to labor market needs.

This regional differentiation underscores that "developing countries" constitute a heterogeneous category requiring context-specific integration frameworks.

## 3. Methodology

This study employs a multi-pronged methodological approach combining systematic literature review with conceptual framework development, balancing empirical grounding with theoretical insight. We conducted a systematic literature review [SLR] to synthesize empirical and theoretical

Table 2
*Regional Differentiation in Generative AI Adoption Challenges and Strategies*

| *Region* | *Representative Countries* | *Primary Adoption Drivers* | *Distinctive Challenges* | *Prevailing Policy Approaches* | *AI Policy Adoption Rate* |
|---|---|---|---|---|---|
| Sub-Saharan Africa | Nigeria, Kenya, South Africa, Rwanda | Leapfrogging potential, donor-funded initiatives, youth demographic dividend | Acute infrastructure gaps (electricity <60% access), limited device ownership, faculty digital literacy gaps | Pilot projects (e.g., AI labs), NGO partnerships, mobile-first solutions, South-South collaborations | <30% |
| South Asia | India, Bangladesh, Pakistan, Sri Lanka | Large youth populations, STEM education emphasis, growing tech industry | Extreme resource inequality, linguistic diversity (1000+ languages), high student-faculty ratios | National AI strategies, public-private partnerships, scale-focused implementations | 40-55% |
| Southeast Asia | Indonesia, Philippines, Vietnam, Thailand | Economic competitiveness, regional integration (ASEAN), manufacturing base | Digital divide urban-rural, varying governance capacities, intellectual property concerns | Regional cooperation frameworks, competency-based integration, industry-academia linkages | 45-60% |
| Latin America & Caribbean | Brazil, Mexico, Colombia, Jamaica | Open education movements, regional collaboration networks, middle-income status | Economic volatility, unequal internet access, faculty resistance to pedagogical change | Institutional networks, OER integration, faculty development programs | ~45% |
| Middle East & North Africa | Egypt, Saudi Arabia, Morocco, UAE | National vision documents (e.g., Saudi Vision 2030), economic diversification | Cultural-linguistic alignment issues, geopolitical factors, varying resource levels | Top-down national initiatives, international partnerships, focus on Arabic NLP | 50-70% (high variation) |

*Note.* Prepared based on UNESCO (2025) regional surveys and institutional reports.

literature on socio-economic and equity dimensions of generative AI in developing country higher education. Given the rapid proliferation of AI research and requirements for methodological transparency, replicability, and structured synthesis (Snyder, 2019), we adopted a systematic review approach following Preferred Reporting Items for Systematic Reviews and Meta-Analyses [PRISMA] 2020 guidelines to ensure rigorous identification, screening, eligibility assessment, and study inclusion (Page et al., 2021).

Beyond procedural rigor, the study incorporates critical interpretive orientation, interrogating structural power asymmetries embedded in global AI production and adoption systems.

### 3.1. Synthesis Protocol

The literature review followed a systematic synthesis approach comprising identification, screening, eligibility examination, and data extraction stages.

#### *3.1.1. Search strategy*

(a) **Databases**. We conducted comprehensive searches across Scopus, Web of Science Core Collection, ERIC, IEEE Xplore, Google Scholar, and institutional repositories (UNESCO, World Bank) to ensure interdisciplinary coverage spanning education, artificial intelligence, development research, and socio-economic policy literature.

(b) **Search Phrases and Boolean Strings**. Search strings incorporated keywords related to artificial intelligence, higher education, and equity:

> ("Generative AI" OR "Artificial Intelligence" OR "Large Language Models" OR "ChatGPT") AND ("Higher Education" OR "Universities" OR "Tertiary Education") AND ("Equity" OR "Digital Divide" OR "Inequality" OR "Global South" OR "Developing Countries" OR "AI Colonialism") AND ("adoption" OR "resistance" OR "integration").

We covered literature from 2020-2026 to capture recent developments while including seminal pre-2020 texts for theoretical foundation.

(c) **Time Frame**. The review included studies from 2020-2026, with 2020 selected as baseline due to accelerated advancements in neural network architectures enabling educational AI applications (LeCun et al., 2015).

(d) **Language Criteria**. We restricted inclusion to English-language publications due to resource limitations and English's dominance in global AI scholarship.

#### *3.1.2. Eligibility and exclusion criteria*

Pre-set criteria ensured transparency and minimized selection bias.

**Inclusion Criteria:** Studies were included if they: (i) were peer-reviewed journal articles or high-quality conference proceedings; (ii) examined AI or generative AI in developing country higher education contexts; (iii) addressed socio-economic, productivity, labor, or equity implications; (iv) presented empirical findings, theoretical analyses, or policy-oriented scholarship from governmental or intergovernmental entities; and (v) were published between 2020-2026.

**Exclusion Criteria:** Studies were excluded if they: (i) focused exclusively on technical descriptions without educational or socio-economic relevance; (ii) were opinion pieces, blog posts, editorials, or non-scholarly commentary; (iii) addressed only K-12 or corporate training contexts; (iv) were duplicates across databases; or (v) presented advocacy literature without evidence-based arguments.

#### *3.1.3. Study selection process and PRISMA flow diagram*

The study selection followed four-phase PRISMA 2020 guidelines (Page et al., 2021), as documented in Figure 1. The process comprised:

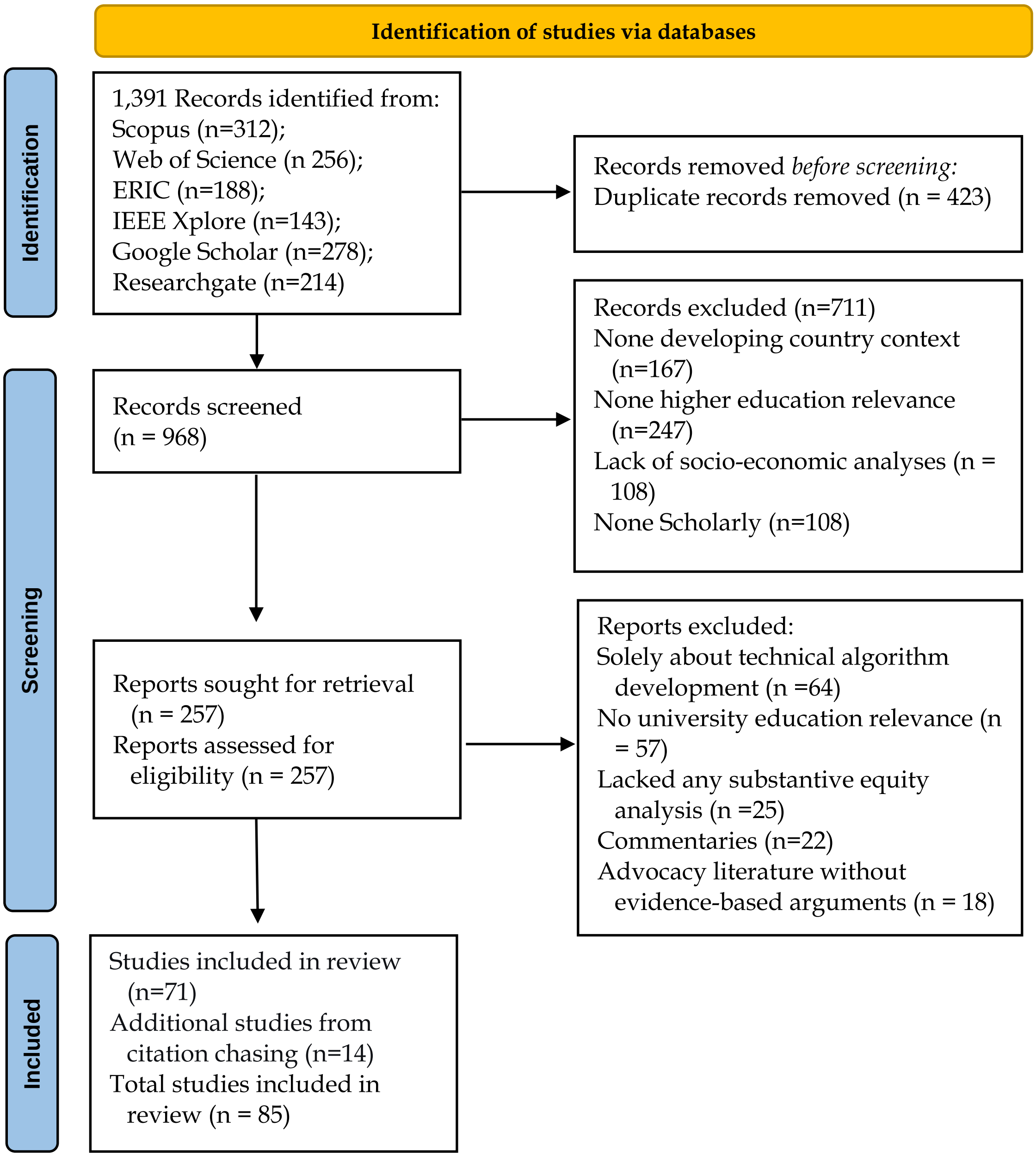
**(i) Identification:** Initial searches across six databases yielded 1,391 records. Supplementary repository searches added 32 records.

**(ii) Screening**: After removing 423 duplicates, 968 unique records underwent title and abstract screening against inclusion criteria, excluding 711 records primarily due to: lack of higher education relevance (n=247), technical papers without educational context (n=189), lack of developing country focus (n=167), and non-scholarly formats (n=108).

**(iii) Eligibility:** 257 full-text articles underwent quality and relevance assessment, excluding 186 articles for: exclusively technical algorithm development (n=64), no university education relevancy (n=57), absence of substantive equity analysis (n=25), non-scholarly (commentaries) (n=22), and advocacy literature lacking evidence-based arguments (n=18).

**(iv) Inclusion:** 71 studies met all eligibility criteria. Backward citation chasing added 14 studies, resulting in 85 studies for thematic analysis.

Figure 1
*PRISMA 2020 Flow Diagram of Study Selection Process*




*3.1.4. Quality appraisal*

Methodological quality was assessed using modified criteria from the Mixed Methods Appraisal Tool [MMAT] (Hong et al., 2018) and Critical Appraisal Skills Programme [CASP] checklist (CASP, 2018), evaluating: (i) research question clarity; (ii) research design appropriateness; (iii) sampling adequacy; (iv) data collection and analysis transparency; and (v) coherence between findings and conclusions. Rather than excluding studies solely for methodological limitations, we incorporated interpretive quality assessments during synthesis.

*3.1.5. Data extraction*

We established a matrix to systematically extract: (i) author(s) and year; (ii) geographic focus; (iii) study design and methodology; (iv) theoretical framework; (v) key findings; (vi) productivity or inequality implications; (vii) policy recommendations; and (viii) limitations. This structured extraction facilitated cross-study comparability and thematic synthesis.

*3.1.6. Data analysis and synthesis*

The research employed thematic synthesis (Braun & Clarke, 2006; Thomas & Harden, 2008) through three stages: (a) initial inductive coding of findings and conceptual arguments; (b) categorization of codes into broader analytical categories; and (c) development of cross-cutting themes expressing patterns and inconsistencies across studies.

Synthesis revealed five primary themes: (i) AI-driven productivity transformation in universities; (ii) digital infrastructure disparities between Global North and South institutions; (iii) algorithmic bias and epistemic exclusion; (iv) academic labor restructuring and precarity; and (v) data extractivism and AI colonialism. Interpretation was informed by Critical Political Economy Theory (Mosco, 2009) and Digital Divide Theory (van Dijk, 2020) to examine structural power asymmetries, AI infrastructure ownership, and global knowledge hierarchies.

*3.1.7. Trustworthiness and rigor*

To enhance credibility and transparency, we: (i) explicitly documented search strategies and criteria; (ii) employed multi-database searches to mitigate publication bias; (iii) implemented formal coding protocols; and (iv) maintained audit trails for inclusion decisions. These procedures support replicability and analytical rigor (Snyder, 2019).

**3.2. Development of a Conceptual Framework**

*3.2.1 Approach*

Building on integrated theoretical models combining TAM, PMT, and SET (Shrivastava, 2025), we propose a contextual acceptance-resistance framework for developing countries' higher education institutions. The model identifies three interconnected dimensions:

i) Structural-Infrastructural Factors: Technology connectivity, device availability, electrical stability, institutional resources, and support systems.

ii) Cultural-Epistemological Factors: Teaching and learning traditions, knowledge value systems, linguistic diversity, and attitudes toward technological development.

iii) Socio-Economic-Political Factors: National development priorities, economic considerations, political contexts, international relationships, and data sovereignty implications.

This framework enables categorical investigation of how factor combinations generate varying institutional and national adaptation and resistance patterns. It differentiates between principled resistance (stemming from ethical or pedagogical concerns) and constrained resistance (arising from resource limitations), requiring distinct intervention strategies.

*3.2.2. Preliminary validation with the experts*

The analytical strength of the proposed framework was further enhanced through expert consultation. Fifteen specialists were selected purposively. Participants comprised university faculty (n=5), AI investigators (n=4), educational technologists (n=3), and national policy guides (n=3). The participants all had direct participation in institutional or national AI-in-education projects.

Experts were given an organized explanation of the 3D framework on the ground (structural–

infrastructural; cultural–epistemological; socio-economic–political) and were requested to:

i)Evaluate its completeness (on a 5 Point Likert scale);

ii) Identify missing determinants;

iii) Assess the clarity of the distinction between principled and constrained resistance; and

iv) Provide examples from their institutional context.

Responses were obtained through an online survey and follow-up interviews via virtual interviews (45–60 minutes).

The following were the findings from the experts' validation process. With regard to the framework completeness, a mean score 4.3/5 was obtained. On the resistance typology clarity, 12 of 15 experts confirmed a distinction between principled and constrained resistance as real institutional debates. The three domains were also found by experts to describe dominant drivers of AI adoption variation.

The experts made the following suggested refinements:

i) Development of implications of faculty labour as an explicit sub-factor, according to the socio-economic dimension;

ii) More transparency in procurement and vendor dependency risks; and

iii) Student agency is recognized as an independent adoption driver.

No expert suggested unloading any fundamental dimension. Rather, feedback enabled the expansion of domains and not reengineering of the structure.

The findings had the following analytical implications. The consultation indicates that this framework exhibits face validity and resonance in specific contexts in developing contexts. Much as it is yet to be statistically generalizable, this validation exercise demonstrates that the framework resonates with practitioner practice and policy thinking. This might be subject to future empirical testing through large scale survey instruments and institutional case studies that allow construct validation/predictive modeling.

#### *3.2.3. Critical engagement*

The paper's claims and proposals underwent critical scrutiny through multiple methodologies. First, the integration framework was evaluated against documented educational technology implementations in developing countries to identify potential constraints. Second, we assessed policy recommendation feasibility given typical resource limitations in developing nation higher education systems. Third, ethical implications were analyzed through normative lenses including social justice, epistemic diversity, and educational equity frameworks.

The methodology acknowledges the analyst's positionality while maintaining professional impartiality through transparent engagement with opposing arguments and limitations. It recognizes developing countries heterogeneity, avoiding homogenizing assumptions while identifying commonalities enabling comparative assessment.

### 3.3. Ethical Considerations

Since the study utilized publicly available secondary sources, formal ethical approval was not required. However, we maintained rigorous ethical standards regarding academic integrity, accurate representation, and proper source citation.

## 4. A Case for Immediate, Strategic Acceptance

The following sections explore generative AI from several perspectives.

### 4.1. Generative AI as Strategic Solution to Persistent Educational Challenges

Generative AI holds significant potential for addressing developing countries' higher education challenges. A primary issue is qualified faculty shortages—UNESCO reports a global deficit of 58 million teachers, disproportionately affecting developing regions (UNESCO, 2025). Intelligent tutoring systems and automated feedback mechanisms could augment teaching capacity, while personalized learning pathways could enhance existing instruction. Indian studies show students using AI-augmented personalized learning tools achieved substantial progress in Hindi and mathematics, demonstrating AI's potential to improve educational outcomes despite resource constraints (Nguyen & LeBoeuf, 2023).

Beyond faculty augmentation, generative AI offers solutions to persistent equity challenges. Geographic disparities in educational quality, STEM participation gaps, and unequal access to academic support could be mitigated through thoughtful AI implementation. AI translators could localize educational materials, while adaptive instructional systems could support students with inadequate secondary preparation. As the World Economic Forum (2024) emphasizes, AI should enhance rather than replace human engagement, a crucial consideration where teacher-student relationships hold cultural significance.

### 4.2. Economic Imperatives and Workforce Skills

The economic case for integrating generative AI into developing countries' higher education is compelling. The International Monetary Fund estimates 40% of global jobs will be affected by AI, increasing demand for AI-literate graduates (World Bank, 2023). If higher education institutions fail to prepare graduates for this evolving labor market, developing nations risk marginalization in the global knowledge economy. Countries like Singapore and South Korea demonstrate how intentional AI investments in higher education enhance global competitiveness through national AI education plans (Lake, 2023).

Developing regions can also leverage generative AI for homegrown innovation rather than merely consuming imported technologies. Integrating AI education with national development objectives in agriculture, public health, environmental sustainability, and cultural preservation enables higher education institutions to develop locally rooted AI applications addressing pressing challenges. This shifts AI from disruptive import to developmental tool aligned with local needs.

### 4.3. The Price of Resistance: Lost Opportunities and Widening Divides

Resisting generative AI integration carries substantial costs for developing nations' educational and economic trajectories. First, institutional reluctance could produce graduates ill-equipped for AI-infused workplaces, contributing to educated youth unemployment and underemployment. Second, failure to critically engage with AI may reinforce technological dependence, relegating developing economies to consumer rather than creator roles in AI ecosystems. Third, resistance forfeits opportunities to apply AI to local problems, such as developing curricula in neglected languages or accelerating priority-sector research.

Most significantly, broad resistance risks entrenching global knowledge production and dissemination inequities. As elite universities in developed countries accelerate AI integration across research methodologies, a developing country's institutions resisting engagement risk exclusion from cutting-edge scholarly discourse and collaboration networks. Conversely, strategic integration enables developing country's scholars to participate in global AI research agendas while ensuring their unique perspectives inform ethical frameworks and application priorities.

### 4.4. Case Examples of Contextual AI Integration

To move beyond purely conceptual discussion, we examine three contrasting case examples illustrating how developing countries' institutions navigate AI adoption midst resource constraints.

#### *4.4.1. Case 1: AI literacy initiative*

Nigeria had 45,000 undergraduate students who faced limited stable electricity. These problems were accompanied by high student-to-faculty ratios and poor facilities in the library. Therefore, from 2023-2024 the university introduced AI literacy in a phased way, reaching 5,000 undergraduate students. Implementation took place in three phases: first, bringing low-bandwidth AI tools in computer labs plus backup generators; second, teaching faculty workshops on AI-assisted assessment; third, integrating AI writing assistants into English composition courses, together with guidelines on ethical use. This phase of implementation includes practical projects for computer programming and AI writing assistant installation on the student floor.

The initiative faced challenges including intermittent internet connections; differing availability of student smartphones; and faculty anxiety about increased workload. To adapt, the university used hybrid offline-online deployment, peer mentoring for various digital skills, and guidelines contextualized in the ethics field. Early evidence of positive results emerged, including 68% of participating faculty reporting grading time improvements, an increase of 42% in student AI literacy scores and a 55% reduction in detected plagiarism in pilot courses, through the university's 2024 annual report and a survey of 85 faculty (The University of Lagos, 2024).

#### *4.4.2. Case 2: AI research partnership at University of São Paulo, Brazil*

University of São Paulo, an AI research-intensive university faced the challenge of a brain drain of AI personnel to the private sector. Its strategic initiative included a North-South partnership of European universities between 2022 to 2025 for the development of Portuguese-language AI for education. The partnership included co-developing Portuguese language models trained on Brazilian academic texts, setting up joint PhD supervision and importantly, negotiating an intellectual property agreement that guaranteed the Brazilian university commercial rights for local applications.

The experience taught important lessons, showing that collaborative models like these can help fill the gaps in traditional models and make progress, but they do need to be thoughtfully negotiated Intellectual Property [IP]. It also reconfirmed that the local language enhances the cultural relevance, and that investment in research capacity building is the precondition of a sustainable AI ecosystem based in the region.

#### *4.4.3. Case 3: Mobile-first AI integration at University of Nairobi, Kenya*

The backdrop of the case was the University of Nairobi, a top East African public university of greater than 70,000 students in Kenya, where mobile access is high but computer laboratory usage is limited. Through a strategy that included lightweight apps for intermittent connectivity; an SMS-based tutoring system; a partnership with telecom provider Safaricom for zero-rated data access; and inclusion of Swahili language processing, the university's "AI-on-Mobile" project, which ranged from 2022 to 2024, tapped into this smartphone ubiquity (Kenya Ministry of Education, 2024; University of Nairobi, 2024).

The project incorporated such novel context-sensitive attributes as data-light AI models, offline functionality, and multi-modal delivery, via SMS, USSD, mobile app, and WhatsApp. It struggled with limited device storage, rural-urban digital literacy divides, power charging problems and some faculty resistance. With all of this in mind, the project had a far-reaching impact: it reached 12,000 students, boosted completion rates on programming courses by 35%, and cut infrastructure costs by 80% compared with a lab-based model. It also pushed for inclusion: 45% of rural students now have access to AI tools for the first time and encouraged innovations in the local context, resulting in three new Swahili AI applications being developed by the new project managers.

Key to that success was the telecommunications partnership that broke down cost barriers, a multi-tiered technical plan, advocacy by faculty champions, and the joint design process with students. The main lessons reinforced the message that mobile-first strategies help overcome infrastructure gaps, that telecom partnerships are a sustainable model of inclusion, lightweight offline tools are critical, and local language integration plays a critical role in relevance and adoption. Table 3 provides a summary of the comparison of the three cases.

These cases demonstrate successful integration requires: (1) adaptive technology matching infrastructure realities; (2) faculty development addressing practical concerns; (3) ethical frameworks responsive to local contexts; and (4) innovative partnerships overcoming resource constraints.

Table 3
*Comparative Insights from Three Cases summary*

| *Dimension* | *Nigeria (Infrastructure-constrained)* | *Brazil (Research-focused)* | *Kenya (Mobile-leveraging)* |
|---|---|---|---|
| Primary Strategy | Computer lab-based with backup power | Research partnership & language models | Mobile-first, telecom partnership |
| Key Innovation | Hybrid offline-online model | Portuguese language AI development | Lightweight mobile AI, SMS integration |
| Main Challenge | Intermittent electricity & internet | Brain drain to private sector | Device storage & digital literacy |
| Scalability | Moderate (requires infrastructure) | Low-moderate (research-intensive) | High (mobile ubiquity) |
| Cost Model | Institutional funding + grants | International partnership funding | Telecom partnership + institutional |
| Cultural Adaptation | Contextualized ethics guidelines | Local language model training | Swahili content & local applications |

## 5. Adoption Challenges in Developing Nation Contexts

### 5.1 Infrastructure and Resource Constraints

The most formidable challenge for generative AI integration in developing country higher education is inadequate digital infrastructure. While 90% of global academics use AI tools professionally (UNESCO, 2025), actual usage in developing countries reveals limitations regarding connectivity, device availability, and classroom electricity. Unlike developed country educators concerned with AI's ethical implications, developing country educators confront more fundamental questions: Does internet connectivity support AI activities? Do students have devices for AI applications? Will electricity remain stable throughout teaching sessions? These material constraints generate pragmatic rather than ideological resistance.

Many developing countries report implementation challenges despite generally positive faculty and student attitudes toward artificial intelligence, as institutional readiness, infrastructure limitations, and policy gaps often hinder large-scale integration (Ajani et al., 2025). This reality necessitates integration approaches accommodating infrastructural heterogeneity, offering multiple implementation routes from high-bandwidth cloud to low-bandwidth edge computing alternatives. Experts identify additional barriers including inadequate technology funding, insufficient teacher training, unreliable power and internet, lack of technical support, and data privacy concerns (DigitalDefynd, 2025).

### 5.2. Cultural and Pedagogical Misalignment

Beyond material constraints, developing countries face significant cultural and pedagogical challenges in embedding generative AI. Most generative AI models are trained on Western texts, potentially embedding cultural ideologies and epistemologies divergent from local knowledge systems. This raises concerns about epistemic colonialism, where AI incorporation inadvertently marginalizes indigenous knowledge while propagating Western intellectual dominance.

Pedagogically, generative AI's content creation and problem-solving capabilities may conflict with educational practices emphasizing knowledge mastery and authoritative teaching. In contexts valuing educational authority (e.g., exam-oriented rote learning), AI systems appearing to bypass traditional learning pathways may generate concern. Additionally, AI-supported collaborative learning could disrupt pedagogical paradigms focusing on individual achievement and competition. These cultural-pedagogical issues require negotiation rather than mere technological implementation. The lack of localized resources and courses—identified as operational obstacles for EdTech in such contexts—underscores that technology alone proves inadequate without cultural inclusion (DigitalDefynd, 2025).

### 5.3. Ethical Issues and Governance Gaps

Developing countries raise legitimate ethical concerns regarding the incorporation of generative AI that extend beyond issues of plagiarism and academic integrity. Emerging scholarship emphasizes structural inequalities, institutional dependency, and governance challenges, particularly in relation to data control and the asymmetrical flow of digital resources between developing and developed contexts (Ajani et al., 2025; Doğan & Talan, 2025). Algorithmic bias presents particularly pressing concerns in regions with diverse ethnic, linguistic, and socioeconomic groups underrepresented in training data.

Most critically, developing countries often lack robust educational AI governance institutions, leaving them vulnerable to accountability, transparency, and recourse deficiencies. While 19% of global higher education institutions have formal AI policies, this figure drops to approximately 45% in Latin America and the Caribbean and below 30% in Sub-Saharan Africa (UNESCO, 2025). This governance gap engenders legitimate institutional leader reluctance, fearing unintended consequences without clear responsible implementation guidelines. African higher education case studies frame this as "algorithmic colonialism," highlighting dependence and control loss dangers (Bailey, 2025). A summary of the challenges is provided in Table 4.

Table 4
*Challenges to Generative AI Adoption in Developing Nation Higher Education*

| *Category of Challenge* | *Specific Barriers* | *Potential impacts of non-Addressal* |
|---|---|---|
| Infrastructural | Inconsistent connectivity, out of stock devices, energy instability | Outreach in neglected areas, further widening of digital divides. |
| Economic | High implementation costs, underfinanced institutions, competing demands | Superficial implementation that is not sustainable, reliance on external financing. |
| Culture - Pedagogical | Existential disconnect, language barrier, pedagogical practices | Superficial implementation, unembedded adoption, faculty and youth resistance. |
| Ethical-governance | Data sovereignty, algorithmic biases, accountability and oversight issues | Breakdown of trust, negative impact on marginalized groups, ethical issues. |
| Human Capacity | Limited AI training for faculty, technical ignorance, lack of support from IT, reluctance of leadership | Implementation failures, unsustainable projects and waste of learning opportunity. |

## 6. Integration Framework and Proposed Solutions

### 6.1. A Phased, Context-Accentuated Integration Framework with Operational Details

The proposed integration framework moves from abstract principles to actionable implementation through three sequenced phases, each with specific activities, timelines, and success metrics as detailed in Table 5.

Feasibility Considerations for Resource-Constrained Institutions:

i) Foundation phase can begin with minimal funding through open-source AI tools, volunteer task forces, and integration with existing digital literacy programs;

ii) Gradual scaling allows iterative learning and adjustment before significant investment;

iii) Partnership models (Section 6.6) can provide external resources while building local capacity; and

iv) Modular implementation enables departments to proceed at varying paces based on readiness and resources.

This operationalized framework in this manner provides concrete steps, realistic timelines, and measurable outcomes that institutions can adapt to their specific contexts.

Table 5

*Operationalized Three-Phase Integration Framework*

| *Phase* | *Timeline* | *Key Activities* | *Responsible Actors* | *Resource Requirements* | *Success Indicators* |
|---|---|---|---|---|---|
| Foundation Phase | Years 0-2 | 1. Infrastructure audit & gap analysis<br>2. Stakeholder consultations (students, faculty, admin)<br>3. AI policy draft with ethical guidelines<br>4. Pilot projects in 2-3 departments<br>5. Basic faculty AI literacy training | AI Task Force (cross-functional), IT Department, Academic Senate | $5K-$50K (depending on institution size), 0.5 FTE coordinator, existing computer labs | • 80% stakeholder awareness<br>• Draft policy document<br>• 2+ pilot projects launched<br>• 30% faculty basic AI literacy |
| Expansion Phase | Years 2-4 | 1. Scale successful pilots to 30% of departments<br>2. Implement AI-enhanced assessment systems<br>3. Develop disciplinary AI integration modules<br>4. Establish AI ethics review committee<br>5. Student AI literacy certification program | Department Chairs, Center for Teaching Excellence, Student Government | $20K-$200K, 1-2 FTE support staff, upgraded internet connectivity | • 50% course integration<br>• Functioning ethics committee<br>• 60% student AI certification<br>• Measured learning outcome improvements |
| Transformation Phase | Years 4+ | 1. Institution-wide AI integration<br>2. Local AI solution development for community challenges<br>3. AI research centers addressing national priorities<br>4. South-South/North-South partnership networks<br>5. AI governance leadership in regional consortia | University Leadership, Research Offices, International Partnerships | $100K-$1M+, dedicated AI center, sustainable funding model | • 80% course integration<br>• 5+ locally developed AI applications<br>• External research funding secured<br>• Policy influence at national level |

### 6.2. Appropriate Technology Solutions for Infrastructure Challenges

Rather than awaiting comprehensive infrastructure upgrades, developing country institutions should pursue appropriate technology approaches functioning within existing constraints. This includes promoting low-bandwidth AI operable with intermittent connectivity, mobile-first solutions recognizing smartphone prevalence even in resource-poor settings, and hybrid models combining internet-based AI tools with offline capabilities. Collaborations with telecommunications providers and technology firms can develop locally viable solutions.

Institutions must also advocate for national digital infrastructure investments aligned with educational visions. By positioning AI as essential for national rather than merely institutional benefit, higher education leaders can drive infrastructure upgrades serving all societal sectors. This advocacy should highlight educational technology investments' multiplier effects, enhancing not only research capacity but also teaching quality and administrative efficiency.

### 6.3. Developing Localized Competency Frameworks

We recommend developing culturally and pedagogically appropriate AI competency frameworks addressing developing countries' specific educational values and developmental concerns. Extending UNESCO's AI competency frameworks for education, such localized equivalents should incorporate indigenous knowledge systems, emphasize locally pertinent ethical considerations, and prioritize use cases addressing regional problems (Valentini & Blancas, 2025).

These competency frameworks should inform curriculum planning, faculty preparation, and assessment across disciplines. Rather than treating AI literacy as isolated skill, integration should emphasize disciplinary infusion, demonstrating how AI tools enrich learning and research across fields from agriculture to zoology. This perspective acknowledges AI's primary educational value lies not in ubiquity but in domain-specific applications advancing disciplinary knowledge and technological fluency.

### 6.4. Establishing Ethical Governance Structures

Developing countries must create appropriate AI education governance frameworks addressing their unique ethical concerns. These frameworks should emphasize:

i) Data sovereignty principles ensuring educational context data storage, processing, and retention within institutional or national settings, with clear cross-border data transfer guidelines;

ii) Algorithmic audit protocols systematically evaluating AI systems for biases, particularly regarding ethnicity, language, gender, and socioeconomic status relevant to local populations;

iii) Transparency requirements mandating disclosure of AI systems' capabilities, limitations, and potential biases to all stakeholders; and

iv) Redress mechanisms providing explicit means for addressing harms from educational AI implementation.

Such governance frameworks should be developed inclusively with faculty, students, administrators, community members, and technology professionals. While international collaborations offer valuable perspectives, governance principles should prioritize local values rather than blindly exporting external policies.

### 6.5. Building Sustainable Implementation Capacity

Sustainable AI integration requires human capacity investments at innovation's core. Faculty training programs should extend beyond technical skills to pedagogical integration, ethical considerations, and critical evaluation of AI outputs. Turkish research suggests faculty self-efficacy with AI tools critically influences willingness to incorporate technologies in teaching (Türk et al., 2025). Development programs should thus build confidence through practical experience and mentoring support. Professional development should be systematic, holistic, and evidence-based, as detailed in specific playbooks documenting effective practices (Lewis Miller et al., 2025).

Student AI literacy programs should combine technical proficiency with critical awareness, equipping students to use AI effectively while understanding limitations and potential biases.

These efforts should permeate curricula, recognizing AI's transformative potential across fields from literature to engineering. Institutions should also develop technical support capacities for ongoing AI system operation, troubleshooting, and reduced contractor dependence. Northeastern University's faculty training focusing on AI technology for learning exemplifies this approach (Schell, 2025).

### 6.6. Fostering South-South and North-South Partnerships

Developing countries should cultivate international partnerships across geographical zones. South-South collaborations offer particular potential as cooperative mechanisms for institutions sharing similar constraints and objectives, enabling resource pooling, collective solution development, and joint advocacy in global AI governance. Well-designed North-South partnerships can provide technical expertise and resource access without creating dependency.

Such partnerships should emphasize skill and capacity transfer rather than mere technology transfer, developing local AI development, application, and governance expertise. Partnership agreements must address intellectual property rights clearly, ensuring joint project innovations benefit all partners. Collaborations should extend beyond institutions to include startups, civil society organizations, and government agencies engaged in educational initiatives. Partnerships can also develop technical solutions to ethical challenges, such as federated learning collaborations enabling model training without centralizing sensitive local data addressing data sovereignty concerns (Bailey, 2025). An implementation framework for such is provided in Table 6.

Table 6
*Implementation Framework for Generative AI Integration into Developing Nation Higher Education*

| *Implementation Pillar* | *Key Components* | *Success Indicators* |
|---|---|---|
| Infrastructure Strategy | Tech Choice, hybrid models, infrastructure advocacy | High accessibility for most users, sustainable maintenance systems. |
| Competency Development | Community level models, disciplinary convergence (disciplinary integration), continuous professional development, | faculty confidence and knowledge, curriculum consistency, student assessment. |
| Ethical Governance | Policy development for all stakeholders, algorithmic audit protocols, transparency mechanisms | Policy roll-out, transparency mechanisms, and policy enforcement rate of adoption, completion of audits and stakeholder satisfaction performance measures. |
| Pedagogical Integration | Adaptation in teaching, pedagogical transformation, assessment and research improvements | Change in learning, evaluation for effectiveness of learning, innovation in teacher education, productivity of research. |
| Partnership Ecosystem | South-South partnerships, fair North-South partnerships, inter-stakeholder cooperation | Sustainability of partnerships, indicators for capacity transfer, combined innovation effects. |
| Sustainability Planning | Economic models, HRM capabilities, scaling strategies | Implementation (beyond pilot testing), institutional investment budgets (after initial cost), leadership buy-in. |

## 7. Discussion

### 7.1. Resisting as the Assessment of Institutional Risk

The findings show that resistance to generative AI in a developing country higher education system is more consistent with institutional risk assessment rather than a categorical rejection. There are concerns with infrastructure stability, data governance, epistemic representation, labor effects, and long-term technology reliance in the literature reviewed and case studies in hand. The latter is consistent with Protection Motivation Theory and socio-technical adoption models that predict perceived risk acts as a moderator for perceived usefulness.

Decision errors have a magnified impact in resource poor systems. This type of investing in infrastructure is often irreversible, and policy mismanagement may take scarce resources away from competing priorities. Institutional reluctance is therefore a matter of cost–benefit calculations under uncertainty, and not of technological conservatism. This aligns with emerging literature suggesting resistance and acceptance frequently coexist at individual and institutional levels, reflecting ambivalence toward complex technological change (Shrivastava, 2025). This is a reorientation of the inquiry from "why resist"? to "when and in what structural and governance terms does adoption seem feasible?".

The examples of Nigeria, Brazil and Kenya lend weight to this interpretation. All institutions selectively and conditionally adopted AI and it was done with appropriate conditions, corresponding with infrastructural capacity, research priorities, or mobile penetration considerations. The adoption occurred not as radical change so much as limited experimentation.

### 7.2. Outside of Binary Adoption Models

The review challenges binaries of acceptance versus resistance models. This shift in institutions' behaviors and behaviors positions the role of them along adoption–resistance continuum on an AI divide spectrum: they both promote certain AI uses at the same time (e.g., literacy training, language model development, mobile tutoring) and restrict other uses (e.g., unsupervised assessment automation).

The hybrid positioning implies that the three domains of interest within the proposed framework, in which they interact, are as such 1) Structural–infrastructural capacity, 2) Cultural–epistemological congruence, and 3) Socio-economic and political factors

The adoption decisions lie in the interplay between these domains, not in any single determinant. It can lead to institutional reluctance through infrastructural adequacy without governance capacity, for example.

In contrast, adequate governance with little infrastructure could lead to phased or mobile-first solutions. The examples demonstrate different pathways. In infrastructure-constrained contexts, hybrid and offline-compatible tools were preferred. Language sovereignty and IP negotiations were considered core of research and academia-industrial contexts. In mobile-rich settings, telecom alliances helped minimize the cost burden. These trends indicate that institutional AI trajectories are path-dependent and context-conditioned, not ideologically constructed.

### 7.3. Governance and the Epistemic Positioning

The fact that they reflect this issue is also suggested in the literature, which confirms that debates about data sovereignty and epistemic representation are not marginal to the debate but structurally embedded within an AI discourse. Generative AI systems are primarily developed in the countries of the Global North, and training corpora are often under-representative, with limited linguistic and cultural diversity. Such institutions in developing countries therefore judge not only technical functioning but longer-term implications on the production of knowledge. And rather than presenting this as antithetical to innovation, the evidence indicates it is negotiation over participation in AI ecosystems. Institutions want to avoid exclusive dependency relationships, and also make sure they get the best of their technological advantages. The Brazilian situation illustrates one route: co-development agreements signed under managed intellectual property agreements. The cases of Kenya and Nigeria demonstrate another: adaptation of externally produced systems within indigenous governance frameworks.

From this analysis, I inferred the idea in a practical sense that developing country institutions are not passive recipients of AI technologies but active agents trying to adjust asymmetrical innovation systems to conditions on the ground.

### 7.4. Interpretation of the Framework's Explanatory Utility

The acceptance–resistance framework proposed in this chapter seeks to explain why institutional adaptation varies across states. Institutional theory suggests that while global norms exert isomorphic pressures, local actors may respond through compliance, adaptation, or resistance depending on normative commitments and structural constraints (DiMaggio & Powell, 1983; Meyer et al., 1997). In this sense, resistance may take the form of principled opposition grounded in ethical or epistemic considerations, or constrained resistance shaped by infrastructural, financial, or knowledge limitations.

It is evident from the literature review that the constrained resistance diminishes as infrastructure investment and human resources are strengthened. Principled resistance needs governance arrangements, honesty and adaptability to local contexts in place of mere technical deployment. Forms can be mixed and lead to phased integration systems. This distinction increases the explaining accuracy as compared to models that consider simply perceived usefulness or perceived ease of use. It is also consistent with the thematic results on the digital divide theory and on political economy.

## 8. Limitations and Future Research Directions

### 8.1. Study Limitations

This research acknowledges several limitations that qualify its findings and recommendations. First, as a systematic review and conceptual analysis, the study synthesizes existing research rather than generating new primary data; while this approach offers a comprehensive overview, it cannot fully capture real-time implementation dynamics or unrecorded institutional experiences. Second, the rapid evolution of generative AI technologies between 2022 and 2025 means that some cited studies may not reflect the most up-to-date tool capabilities or current adoption patterns. Third, the focus on English-language publications may introduce language bias by overlooking relevant research published in local languages, particularly in Latin America (Spanish/Portuguese) and Francophone Africa. Finally, although the analysis differentiates broad regional patterns, substantial within-region diversity—such as differences between research-intensive and teaching-focused universities—requires more granular investigation.

### 8.2. Future Research Agenda

To address these limitations and advance the field, we propose several future research directions. First, comparative case studies should be conducted through in-depth qualitative investigations of approximately 10–15 institutions across different developing regions to identify context-specific success factors and implementation barriers. Second, longitudinal implementation research is needed to track institutions over a 3–5 year period as they progress through integration phases, enabling the measurement of educational outcomes and broader institutional change. Third, the proposed acceptance–resistance framework should be validated empirically through approaches such as Delphi studies, survey instruments that capture different resistance types, and network analyses examining how resistance factors interconnect. Fourth, cost–benefit analyses should examine implementation economics across varying institutional types, with particular attention to sustainable financing models suitable for resource-constrained environments. Fifth, local knowledge integration research should explore effective methods for incorporating indigenous knowledge systems into AI education and development processes. Finally, policy transfer studies should investigate how AI education policies from early-adopting developing countries can be adapted and translated to other national and institutional contexts. By addressing these gaps, the academic community can move beyond normative frameworks toward evidence-based implementation strategies that respect the diversity of higher education in developing countries while harnessing AI’s transformative potential.

## 9. Conclusion

This paper argues that developing country higher education institutions' hesitation toward generative AI reflects not failure to recognize technological potential but authentic, critical engagement with complex implementation challenges. Our analysis shows developing countries confront intensified forms of global AI integration issues alongside specific concerns about cultural relevance, technological dependence, and equitable access. Rather than dismissing resistance as backwardness, strategic integration approaches must take these concerns seriously and develop context-sensitive solutions.

The integrated approach proposed emphasizes phased deployment, localized competency building, ethical governance mechanisms, and partnerships facilitating sustainable embedding. Through such frameworks, developing country institutions can harness AI's transformative potential without undermining legitimate equity, sovereignty, or cultural integrity concerns. This understanding recognizes developing countries' decision challenge extends beyond simple acceptance or refusal to choosing between passively receiving externally developed technologies and actively crafting AI ecosystems attuned to local needs.

Future work should examine implementation case studies across different developing country models to identify success factors and ongoing challenges. Long-term evidence about AI's effects on educational attainment, research productivity, and graduate employability would strengthen policy decisions. Research into innovative financing models for educational AI in resource-constrained environments could also identify sustained deployment obstacles.

As generative AI advances unprecedentedly, developing countries face a pivotal moment. Critical, strategic incorporation offers opportunities to enhance educational quality, broaden access, and align with national developmental priorities. Conversely, broad resistance risks excluding developing country institutions and graduates from AI-driven knowledge economies. The optimal path forward involves neither uncritical assimilation nor unprincipled rejection but critical engagement utilizing AI's potential while advocating for ethical, equitable, and culturally responsive appropriation.

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