

Original Research Article

From Digital Divide to AI Divide: A Sociological Study of Educational Inequality in Indian Higher Education

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Abstract

The rapid diffusion of Artificial Intelligence (AI) tools into higher education has introduced a new axis of inequality that extends beyond the conventional “digital divide.” While earlier scholarship focused on disparities in internet connectivity and device ownership, this study argues that access alone no longer captures the full picture of educational inequality in the AI era. It proposes the concept of an “AI Divide” — a multidimensional gap encompassing who has access to AI tools, who possesses the digital literacy to use them effectively, who derives genuine academic benefit, and how these disparities generate new forms of exclusion.

Situated within Indian higher education — a context marked by significant socioeconomic, regional, and institutional diversity — the study draws on a randomly sampled cohort of 111 students to examine AI tool adoption, competence, and perceived academic impact. It investigates the factors shaping unequal access, disparities in skills required for effective academic use, variation in reported academic benefit, and the mechanisms through which AI adoption creates or reinforces existing educational inequalities.

Drawing on the sociology of education and digital-inequality literature — including cultural capital, the “second-level digital divide,” and algorithmic literacy — this research moves the discourse from a binary

understanding of access to a nuanced analysis of usage, skill, and outcome disparities, contributing to policy discussions on equitable AI integration in the Global South.

Keywords: Artificial Intelligence (AI), AI Divide, Digital Inequality, Digital Literacy, Educational Inequality, Cultural Capital.

1. Introduction

Technology has become central to higher education, reshaping how students learn, communicate, and access knowledge. Computers, the internet, and AI have made education more accessible and efficient, but these benefits are not equitably distributed. Disparities in access to technology, resources, and skills have created persistent educational inequalities — the classic “Digital Divide” that left rural, economically disadvantaged, and under-resourced students struggling to access online learning, a gap starkly exposed during the COVID-19 pandemic.

The rapid advancement of AI has introduced a new phase of this problem. Tools such as ChatGPT, Google Gemini, Microsoft Copilot, and Grammarly are now widely used in higher education for research, writing, coding, and personalised learning. Yet this leap has produced a new challenge: the AI Divide — unequal access to AI tools, AI literacy, and the ability to integrate them effectively into academic work. Socio-economic background, geography, institutional facilities, and language proficiency all shape a student’s capacity to benefit from AI, marking a qualitative shift from access-based to literacy-based inequality.

This study, “From Digital Divide to AI Divide,” argues that access to hardware is no longer sufficient; AI literacy and institutional support are now the primary determinants of academic success. It aims to provide empirical insight to guide inclusive policy, promote AI literacy, and ensure equitable access to AI-based resources.

1.1 Objectives of the Study

- Objective 1: To examine the impact of AI on educational inequality among students in Higher Education Institutions (HEIs).
- Objective 2: To identify the factors that create unequal access to AI technologies in higher education.
- Objective 3: To analyse the opportunities and challenges of using AI in teaching and learning.
- Objective 4: To suggest measures for promoting equal and inclusive access to AI-based educational resources.

1.2 Theoretical Perspectives

The study draws on two complementary lenses. The Digital Divide / Second-Level Digital Divide framework (Warschauer, 2003; Ragnedda & Muschert, 2013) distinguishes first-level access (devices, connectivity) from second-level disparities in skills, usage, and the ability to convert access into meaningful benefit. Cultural Capital theory (Bourdieu; extended by Ritzer & Sam, 2014) explains how family background, prior exposure to technology, language, and socio-economic position shape comfort and competence with new technologies independent of formal access. Together, these predict that even widespread AI access will not eliminate disparities in confidence, training, and institutional support — the hypothesis tested against the survey data below.

1.3 Significance of the Study

The study is significant because it examines the transition from the Digital to the AI Divide and its impact on educational inequality in HEIs. Educationally, it clarifies how AI is reshaping teaching and learning; socially, it

examines how language and social background affect access and use. For students, institutions, and policymakers, the findings support AI literacy programmes, inclusive policy, and equitable access.

2. Review of Literature

This review synthesises international and national scholarship, and doctoral work, organised thematically to connect conceptual threads to the theoretical perspectives above and the study's objectives.

2.1 From the Digital Divide to the Second-Level Divide

Warschauer (2003) challenged the binary framing of access versus non-access, arguing that physical access does not automatically translate into benefit and proposing a continuum shaped by content, language, literacy, and institutional structure. This gave rise to the “second-level” digital divide, consolidated by Ragnedda and Muschert (2013), which shifts focus from who has access to who can convert it into skill, usage, and outcomes. Ireland and Lestari (2025) caution that simple hierarchies of “more” or “less” useful skills can obscure the deeper structures of power and institutional support that determine whose use of technology converts into better outcomes. This literature supplies the scaffolding for the present study's AI Divide argument: owning an AI account is not the same as possessing the literacy to use it for genuine academic advantage, which is why the questionnaire asks about barriers, language, and perceived equity separately from ownership.

2.2 Cultural Capital and Caste

Bourdieu's concept of cultural capital explains why second-level disparities track existing social hierarchies rather than appearing at random. Ritzer and Sam (2014) extend this lens into digital space, showing how caste identity and exclusion are reproduced through online platforms rather than dissolved by them — a corrective to any assumption that digital and AI environments are socially neutral. This directly informs the decision to measure caste and language, alongside cost and connectivity, as distinct predictors of disadvantage. It also anticipates a recurring finding in this study's open-ended responses: students describe paid AI subscriptions as unaffordable for middle-class families even when a free tier is nominally “available,” illustrating how economic and informational resources shape practical benefit quite apart from formal accessibility.

2.3 Algorithmic Literacy

Selwyn (2011) cautions against technologically deterministic narratives, insisting that the social relations surrounding a technology — who is trained, whose knowledge is valued, which institutions invest in support — determine its educational effects. Shi, Selwyn, Eynon and Knox (2026) build on this to theorise algorithmic literacy as a distinct, teachable competence, distinguishing the capacity to understand and critically use AI from the narrower ability to operate an application. This supplies the vocabulary for the second-level gap this survey was designed to detect: the near-tie between “lack of AI knowledge” and “lack of internet access” as top barriers (Section 5.2), and the strong demand for a formal AI curriculum (Section 5.4), both empirically confirm this literature's prediction that literacy gaps widen unless institutions actively teach algorithmic literacy rather than assume it develops through everyday use.

2.4 AI and Educational Inequality: Global Perspectives

Michel (2020) establishes that AI's effects, like earlier technological waves, are unlikely to be evenly distributed. Bulathwela, Pérez-Ortiz, Holloway and Shawe-Taylor (2021) caution that AI's benefits so far accrue mainly to students already positioned to use it well, and that without deliberate socio-technical design, AI could increase

rather than level educational inequality. García-Alonso (2025) extends this by showing how algorithmic governance embedded in educational AI systems can itself reproduce inequality, shifting disadvantage from device to algorithm. From a Global South vantage point, Azim and Thory document how infrastructural constraints, cost, and language compound one another, while Hodøl (2025) reports that educators increasingly perceive the meaningful divide as one of ability and support rather than ownership. Bouakaz and Khalid (2025) situate classroom AI adoption within wider debates about power, access, and pedagogy. Together, this literature establishes that AI widening educational inequality is not speculative but already documented — the premise this study tests within Indian higher education — and repeatedly calls for deliberate institutional and policy intervention rather than placing responsibility on individual students.

2.5 The Indian Context

Patgiri (2026) argues most pointedly that for students lacking digital and cultural capital, AI is a “dangerous helper” whose careless use is more likely to expose them to academic risk than deliver the benefits enjoyed by better-supported peers — anchoring this study’s proposition that access without literacy can itself become a source of disadvantage. Earlier India-focused research supplies the empirical baseline: Banwari and Singh (2024) document rural–urban infrastructure disparities; Singh (2022) maps access and equity nationally; and Kumari, Singha and Gardia (2024) extend this to identity and knowledge access. Doctoral work adds depth — Dubey (2024) on institutional AI adoption, Devadas (2025) on caste and digital technology in Kerala, Ma (2017) on cross-country digital learning inequality, and Bhattacharya (2025) on digital technology and education more broadly. Collectively, this literature confirms that the building blocks of an AI Divide — uneven infrastructure, caste-linked disadvantage, and skills gaps — are well documented, but none combines these variables within a single survey of a randomly sampled, multi-institution student cohort specifically about AI, which is precisely the gap this study’s questionnaire is designed to close.

3. Research Gap

Much prior research studied the Digital Divide and AI separately, with comparatively little sociological work examining how digital inequalities are transforming into an AI Divide within higher education. Most studies examine access, skills, and outcomes in isolation; a comprehensive study connecting digital access, AI literacy, language, gender, and caste in the Indian context remains limited.

Guiding Research Question: “Does having access to digital technology and AI tools actually lead to equal educational opportunities and outcomes, or does a new AI/digital-skills divide continue to reproduce educational inequality among higher-education students in India?”

This study contributes by examining the shift from the Digital Divide to the AI Divide sociologically, connecting **access, literacy, affordability, language, gender, and caste to understand how these factors shape educational opportunity** in Indian higher education.

4. Research Methodology

The study employed a primary data collection strategy using a structured questionnaire administered via Google Forms. The instrument covered AI usage patterns, perceived barriers (cost, connectivity, knowledge), and language, gender, and caste dimensions of AI access.

5. Data Analysis and Presentation

This section presents the survey findings and interprets each in relation to the study's four objectives and the theoretical perspectives outlined in Section 1.2.

5.1. AI Tool Adoption

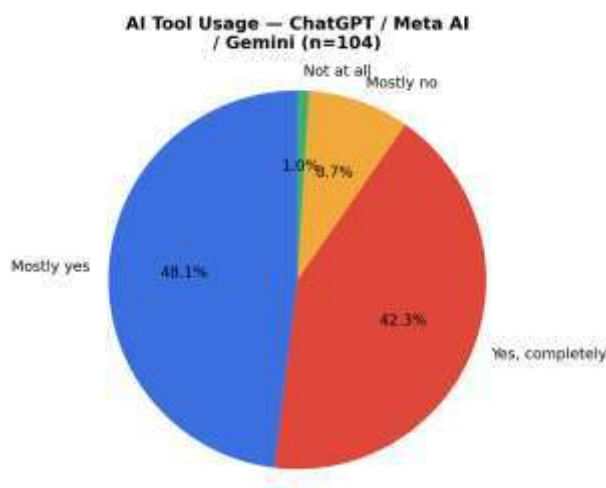


Figure 1: Do you use AI (ChatGPT, Meta AI, Gemini)?

90.4% of respondents use AI either “mostly” (48.1%) or “completely” (42.3%); only 8.7% use it rarely and 1% not at all. This near-universal first-level access confirms Objective 1’s premise, but high adoption alone does not indicate equal benefit — the questions below probe the gap between access and effective use (Objective 2).

5.2. Barriers to Effective AI Use

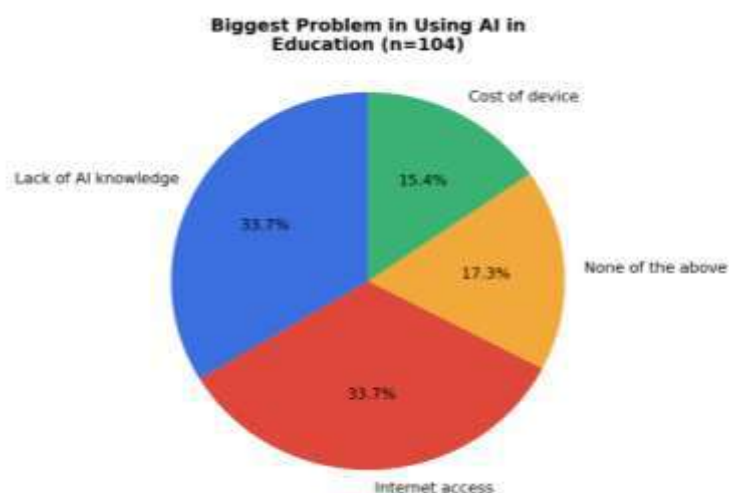


Figure 2: Biggest problem in using AI in education

Lack of AI knowledge (33.7%) and internet access (33.7%) are tied as the most-cited barriers, ahead of device cost (15.4%); 17.3% reported no problem. The near-tie between a connectivity (first-level) and a knowledge (second-level) barrier is a direct empirical marker of the second-level digital divide, addressing Objectives 2 and 3. Open-ended responses on subscription affordability reinforce this: students described paid AI subscriptions as

unaffordable for middle-class families and recommended subsidised subscriptions, free workshops, and curriculum integration — evidence consistent with a cultural-capital explanation of unequal practical benefit.

5.3. Language

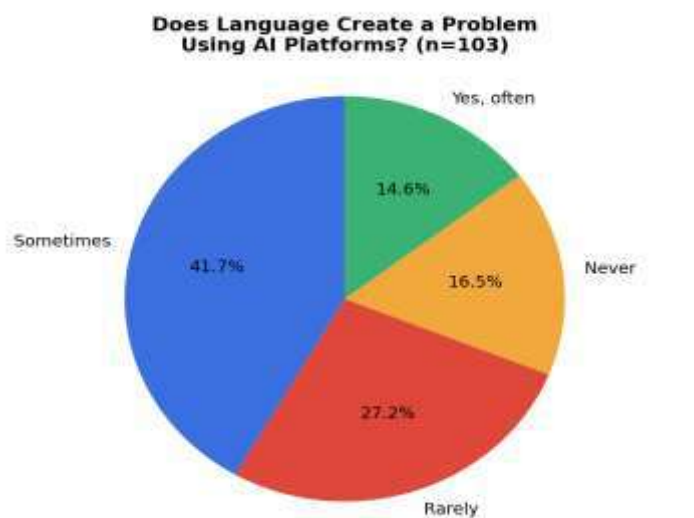


Figure 3: Does language create a problem using AI platforms?

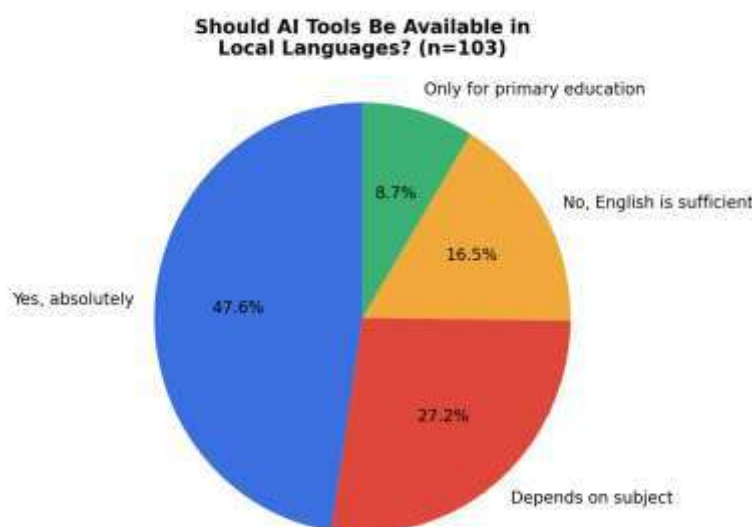


Figure 4: Should AI tools be available in local languages?

41.7% of respondents face language-related difficulty “sometimes,” and 14.6% “often” — together over half the sample; only 16.5% never face this problem. 47.6% want local-language AI tools “absolutely,” and 27.2% say it depends on the subject. Language functions as a form of linguistic capital: students without strong English proficiency face an additional, largely invisible layer of the AI Divide not solved by devices or connectivity alone, supporting Objective 2 and pointing to an actionable barrier for Objective 4.

5.4. AI in the Curriculum

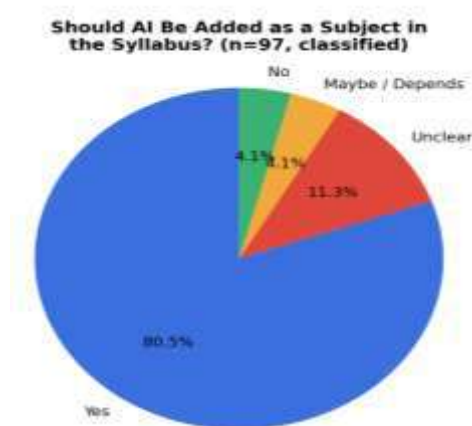


Figure 5: Should AI be added as a subject in the syllabus?

80.4% of respondents support adding AI as a formal subject, citing digital-skill building, ethical use, and career preparation. This operationalises algorithmic literacy directly — students are articulating demand for structured AI education, precisely the second-level intervention theory suggests is needed to close the AI Divide (Objectives 3 and 4).

5.5. Gender

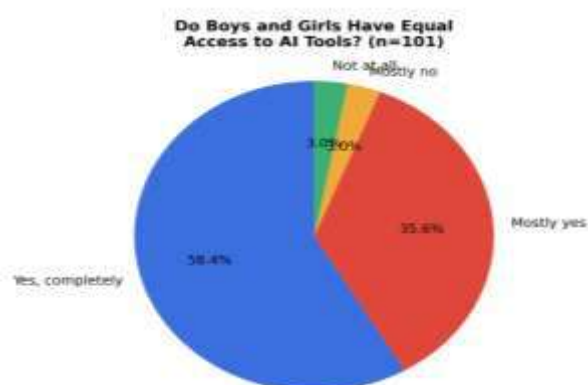


Figure 6: Do boys and girls have equal access to AI-based education tools?

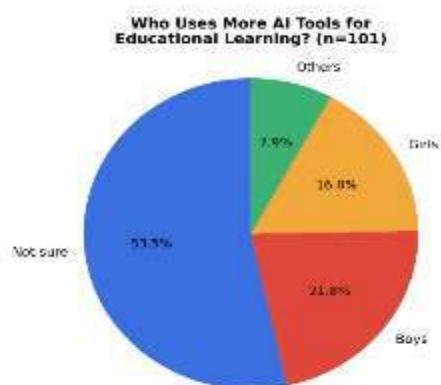


Figure 7: Who uses more AI tools for educational learning?

58.4% perceive completely equal access by gender and 35.6% say “mostly yes”; only 6% perceive meaningful inequality. Over half (53.5%) were unsure which gender uses AI more, while 21.8% named boys and 16.8% named girls. Gender does not emerge as a strong axis of the AI Divide in this sample, nuancing Objective 2: not every social variable produces a visible divide equally.

5.6. Caste

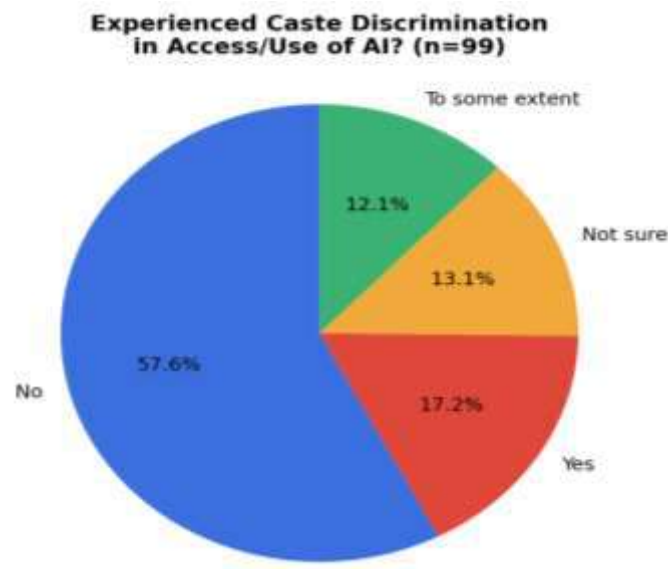


Figure 8: Experienced caste discrimination in access/use of AI?

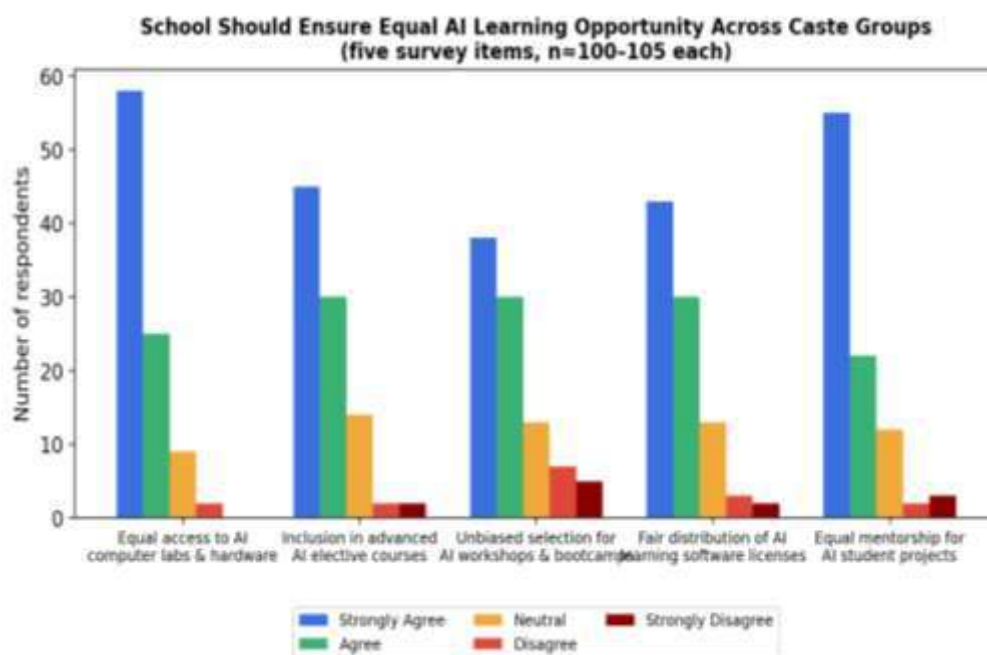


Figure 9: Support for equal AI learning opportunity across caste groups

While 57.6% report no experience of caste discrimination in AI access, a combined 29.3% report experiencing it directly (17.2%) or “to some extent” (12.1%). This sociologically significant minority indicates caste persists as a live dimension of the emerging AI Divide (Objective 2). Despite this, support for caste-inclusive AI policy is very high across all equity items — equal access to labs and hardware, inclusion in electives, unbiased workshop selection, fair

licence distribution, and equal mentorship — showing readiness for institutional intervention (Objective 4) even as lived experience shows the divide is not yet closed along caste lines.

6. Key Findings

- AI adoption is near-universal (90.4% use AI mostly or completely), confirming first-level access is no longer the primary barrier for most students.
- Barriers are now predominantly second-level: lack of AI knowledge ties with internet access as the top-cited problem (33.7% each), ahead of device cost (15.4%).
- Language remains a substantial, under-addressed barrier: over half face at least occasional difficulty, and nearly half want local-language AI platforms.
- Near-universal support (80%+) for formally teaching AI as a subject indicates latent demand for structured algorithmic-literacy education.
- Gender-based access is perceived as largely equal (94% completely/mostly equal), making gender a comparatively minor axis of the AI Divide.
- Caste remains a live concern: almost 3 in 10 report experiencing caste discrimination in AI access, even though support for caste-inclusive policy is near-universal.

7. Conclusion and Recommendations

The analysis confirms the study's central argument: the transition from the Digital Divide to the AI Divide is well underway. Basic access is now widespread, but the data — read through the second-level digital divide, cultural capital, and algorithmic literacy — show that knowledge, language, affordability, and caste continue to determine who genuinely benefits from AI, validating the study's objectives and its premise that hardware access is no longer sufficient.

Based on these findings, the study recommends:

- Structured AI-literacy training and workshops, prioritised for students who self-report low AI knowledge.
- Subsidised or free AI-tool subscriptions and free/low-cost campus internet access, addressing the tied top two barriers.
- Development and promotion of local-language AI interfaces and learning tools.
- Formal integration of AI education into the syllabus, responding to strong (80%+) student demand.
- Explicit caste-inclusive policies for AI lab access, workshop selection, software licensing, and mentorship.

These findings affirm that the AI Divide is best understood not as a single access gap but as a layered set of second-level disparities — in knowledge, language, affordability, and social background — requiring equally layered, multidimensional policy responses.

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