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Artificial Intelligence and the Reproduction of Educational Inequality: The Role of Digital Capital among University Students in India

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ABSTRACT

Artificial intelligence (AI) tools are rapidly reshaping how university students learn, yet the benefits of these tools may not be equally distributed. Grounded in Bourdieu's theory of capital and social reproduction and in digital capital theory (Ragnedda, 2018), this study examines whether digital capital shapes the perceived reproduction of educational inequality through the sequential mechanisms of AI literacy and AI usage for learning. A quantitative, cross-sectional survey was administered to 410 university students enrolled in undergraduate programmes in India. Exploratory Factor Analysis confirmed a clean four-factor structure (KMO = .886; Bartlett's $\chi^2(190) = 3005.49$, $p < .001$), and Confirmatory Factor Analysis in AMOS established satisfactory reliability and validity (Cronbach's α = .803–.846; composite reliability = .804–.846; discriminant validity confirmed via the Fornell–Larcker criterion and Heterotrait-Monotrait ratios, all below .60). Structural Equation Modelling revealed that Digital Capital significantly and positively predicted AI Literacy ($\beta = .502$, $p < .001$), which in turn predicted AI Usage for Learning ($\beta = .581$, $p < .001$), which significantly predicted Educational Inequality Perception ($\beta = .529$, $p < .001$). The direct path from Digital Capital to Educational Inequality Perception was non-significant ($\beta = -.064$, $p = .292$), while the standardized serial indirect effect through AI Literacy and AI Usage was significant ($\beta = .154$, 95% CI [.114, .206], $p = .001$), indicating full mediation. These findings suggest that unequal digital capital shapes perceptions of AI-driven educational inequality almost entirely through the literacy-usage pathway rather than through direct access alone, with implications for equitable AI integration in Indian higher education.

Keywords: Digital Capital, Artificial Intelligence Literacy, AI Usage for Learning, Educational Inequality, Digital Divide, Structural Equation Modelling, India

1. INTRODUCTION

The rapid diffusion of artificial intelligence (AI) into higher education has transformed how students research, write, revise, and reason through academic problems. Since the public release of large-scale generative AI tools in late 2022, adoption among university students has grown at an unprecedented pace, with surveys across multiple countries reporting that more than half of undergraduates now use AI tools routinely for coursework (Beckman, Apps, Howard, et al., 2025). AI is frequently promoted as a democratizing force in education: adaptive tutoring, instant feedback, and low-cost access to explanation and revision support are said to hold particular promise for students who lack access to private tutoring, well-resourced libraries, or highly educated family members.

Yet an emerging body of evidence suggests that the benefits of AI in education are not being captured equally. Rather than levelling the playing field, differential access to devices, connectivity, and the skills needed to use AI tools critically and effectively appears to be reproducing, and in some cases amplifying, pre-existing educational advantages. A recent UK-wide survey found that students from the most privileged backgrounds were markedly more likely to use generative AI for assessments than their less privileged peers (HEPI & UCAS, cited in Bowden, 2024), and systematic evidence mapping of generative AI in higher education has identified inadequate infrastructure, low AI literacy, and economic constraints as recurring barriers to equitable adoption (Beckman et al., 2025). This dynamic echoes a well-documented pattern in the broader digital divide literature: once basic access gaps narrow, deeper and more consequential divides emerge in digital skills, in patterns of use, and ultimately in the outcomes that use produces (van Dijk, 2005, 2020; DiMaggio & Hargittai, 2001).

Pierre Bourdieu's (1986) theory of capital and social reproduction offers a powerful lens for understanding this dynamic. Bourdieu argued that individuals who already possess greater economic, social, and cultural capital are able to convert that capital into further advantage within ostensibly meritocratic institutions such as schools and universities, thereby reproducing social inequality across generations. Building on this tradition, Ragnedda (2018, 2020) has proposed digital capital as a distinct form of capital in the Bourdieusian sense: an accumulation of digital competencies and externalized digital resources that can be converted into other forms of advantage, both online and offline. Extending this logic to the current moment, this study argues that digital capital similarly conditions who is positioned to convert AI tools into academic advantage, and that this conversion process occurs through the sequential development of AI literacy and its translation into sustained AI usage for learning.

The Indian higher education context makes this question especially pressing. Government data show that only around half of Indian schools have functional computers or internet access, with a roughly 24-percentage-point gap between urban and rural connectivity (Government of India, Ministry of Education, 2024), and national inequality reporting shows internet usage among the rural population running more than 30 percentage points behind urban usage (Oxfam India, 2022). India's National Education Policy 2020 explicitly calls for technology-enabled learning as a route to making India a "global knowledge superpower" (Government of India, Ministry of Education, 2020), yet the policy's success in practice depends on whether digitally disadvantaged students can access and meaningfully use the very technologies the policy champions. Understanding how digital capital shapes AI literacy, AI usage, and perceptions of educational inequality among Indian university students is therefore both theoretically important and practically urgent.

Despite growing interest in AI adoption in education, most existing research has examined either the determinants of AI acceptance (typically through technology-acceptance frameworks) or the pedagogical effectiveness of AI tools, with comparatively little attention paid to the specific sequential mechanism by which pre-existing digital resource gaps convert into AI-related advantage or disadvantage. This study addresses that gap by proposing and testing a serial mediation model in which Digital Capital shapes AI Literacy, which shapes AI Usage for Learning, which in turn shapes students' perceptions of educational inequality, alongside a direct path from Digital Capital to Educational Inequality Perception. The remainder of the paper reviews the relevant theory and literature, develops five hypotheses, describes the methodology, reports the results of exploratory and confirmatory factor analysis and structural equation modelling, and discusses the theoretical and practical implications of the findings for equitable AI integration in higher education.

2. LITERATURE REVIEW

2.1 Digital Capital and AI Literacy

Digital capital refers to the accumulation of digital competencies (information, communication, safety, content-creation, and problem-solving skills) together with externalized digital technology and resources that can be converted into other forms of advantage (Ragnedda, 2018). Building directly on Bourdieu's (1986) forms-of-capital framework, this perspective treats digital resources and skills as a capital in their own right, one that can be inherited, accumulated, and converted much like economic or cultural capital (Ragnedda & Ruiu, 2020; Ignatow & Robinson, 2017). Van Dijk's (2005, 2020) resources and appropriation model similarly distinguishes successive layers of digital advantage: motivational access, material access, skills, and usage, each of which builds cumulatively on the one before it.

AI literacy — defined as the set of competencies that enable individuals to critically evaluate AI technologies, communicate and collaborate effectively with AI, and use it as a tool in daily and academic life (Long & Magerko, 2020) — can be understood as a specialised, higher-order digital competency that is unlikely to develop in isolation from broader digital capital. Students who already possess reliable device and connectivity access, general digital fluency, and confidence in adapting to new technologies are better positioned to acquire the specific conceptual and evaluative skills that AI literacy demands, mirroring the well-established finding that general digital skills are a strong antecedent of more specialised technology competencies (van Deursen & van Dijk, 2014). Recent survey evidence on generative AI in higher education similarly reports that students' self-reported AI literacy is stratified by prior technology access and socio-demographic background (Beckman et al., 2025).

H1: Digital Capital has a significant positive effect on AI Literacy.

2.2 AI Literacy and AI Usage for Learning

A recurring finding in digital-skills research is that skill precedes and predicts sustained, effective use: individuals who understand how a technology works and what its limitations are tend to use it more frequently, more confidently, and for a wider range of purposes (van Deursen & van Dijk, 2014; van Dijk, 2020). Applied to AI, students who understand core AI concepts, recognise the strengths and weaknesses of AI-generated output, and can evaluate the reliability of AI responses (Long & Magerko, 2020) are better equipped to integrate AI tools productively into their academic routines, whereas students with limited AI literacy may either avoid AI tools altogether or use them uncritically. Holmes, Bialik, and Fadel (2019) similarly argue that the pedagogical promise of AI in education is realised only when learners possess sufficient conceptual understanding to direct and interpret AI systems appropriately. Consistent with this reasoning, this study proposes that AI literacy is a proximal driver of the extent to which students draw on AI tools for learning.

H2: AI Literacy has a significant positive effect on AI Usage for Learning.

2.3 AI Usage for Learning and Educational Inequality Perception

Whether AI usage narrows or widens educational gaps is a central and unresolved question in the emerging literature. Optimistic accounts emphasise AI's potential to expand access to explanation, feedback, and open educational resources, particularly for students in resource-constrained settings (Holmes et al., 2019). However, a growing number of empirical studies point in the opposite direction: because effective AI usage itself depends on prior literacy, access, and confidence, the students who use AI most extensively and most effectively tend to be those who were already advantaged, so that AI usage functions less as an equalizer than as an amplifier of existing gaps (Williamson & Eynon, 2020; Beckman et al., 2025). The 2025 EDUCAUSE AI Landscape Study explicitly frames this pattern as a "digital AI divide," documenting systematic disparities in AI-related resources and adoption across institutions and student groups. In this study, Educational Inequality Perception captures the extent to which students themselves perceive that unequal access to AI and digital resources translates into unequal learning opportunities and academic outcomes. Where students use AI more extensively for learning, and are simultaneously aware of the resource and skill preconditions that made that usage possible, they are expected to more strongly perceive that AI is contributing to the reproduction of educational inequality.

H3: AI Usage for Learning has a significant positive effect on Educational Inequality Perception.

2.4 Digital Capital and Educational Inequality Perception: Direct and Mediated Pathways

Bourdieu's (1986) reproduction theory holds that capital rarely produces advantage in a single step; rather, one form of capital is progressively converted into another until it manifests as a durable, visible advantage or disadvantage. Applied to the present model, this suggests that digital capital's association with perceptions of educational inequality should operate primarily indirectly, through the sequential conversion of digital capital into AI literacy and then into AI usage, rather than through a direct, unmediated channel. At the same time, it remains plausible that digital capital exerts some direct influence on perceived inequality independent of AI literacy and usage — for instance, students who lack basic digital resources may perceive inequality in the education system generally, irrespective of their specific AI literacy or usage levels. Both possibilities are therefore tested explicitly.

H4: Digital Capital has a significant direct effect on Educational Inequality Perception.

H5: AI Literacy and AI Usage for Learning sequentially mediate the relationship between Digital Capital and Educational Inequality Perception.

3. METHODOLOGY

3.1 Research Design

This study employed a quantitative, cross-sectional survey design, consistent with established conventions for testing theoretically derived structural models in the social sciences (Hair, Black, Babin, & Anderson, 2019). A positivist epistemological stance was adopted to permit systematic statistical testing of the hypothesised relationships among Digital Capital, AI Literacy, AI Usage for Learning, and Educational Inequality Perception. A cross-sectional design was judged appropriate for examining the contemporaneous structure of relationships among these constructs, although, as discussed in the limitations, it precludes strong causal inference.

3.2 Sampling and Data Collection

The target population comprised undergraduate university students in India. Data were collected using a structured, self-administered questionnaire built around a five-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree). The final usable sample consisted of 410 students drawn from a range of undergraduate courses, institution types, and rural and urban residence backgrounds, yielding a sample size well above the commonly cited minimum threshold of 200 for structural equation modelling applications (Hair et al., 2019) and above the 10:1 respondent-to-parameter heuristic for the 20-item measurement model estimated here.

3.3 Sample Profile

Table 1 presents the demographic profile of respondents. The sample was fairly balanced by gender (54.

9% female, 42.4% male, 2.7% other) and was concentrated in the 18–23 age range (80.8% of respondents). Students were drawn across BA, BCom, BBA, BSc, and other undergraduate courses, with a slightly larger share of respondents residing in rural areas (52.9%) than urban areas (47.1%). Household income was concentrated in the lower-to-middle bands, with 67.8% of families reporting a monthly income at or below Rs. 50,000. Reported AI tool usage frequency was broadly distributed, ranging from 6.6% who reported never using AI tools to 23.4% who reported daily use, and respondents were drawn from government (47.1%), aided (17.8%), and private (35.1%) institutions.

Table 1
Demographic Profile of Respondents (N = 410)

Variable	Category	n	%
Gender	Male	174	42.4%
	Female	225	54.9%
	Other	11	2.7%
Age	Below 18 years	28	6.8%
	18–20 years	200	48.8%
	21–23 years	131	32.0%
	Above 23 years	51	12.4%
Course of Study	BA	91	22.2%
	BCom	117	28.5%
	BBA	83	20.2%
	BSc	82	20.0%
	Others	37	9.0%
Residence	Rural	217	52.9%
	Urban	193	47.1%
Family Monthly Income	Below Rs. 20,000	129	31.5%
	Rs. 20,001–50,000	149	36.3%
	Rs. 50,001–1,00,000	91	22.2%
	Above Rs. 1,00,000	41	10.0%
Frequency of AI Tool Usage	Never	27	6.6%
	Occasionally	83	20.2%
	Monthly	86	21.0%
	Weekly	118	28.8%

Variable	Category	n	%
	Daily	96	23.4%
Institution Type	Government	193	47.1%
	Aided	73	17.8%
	Private	144	35.1%

Note. N 410 university students.

3.4 Measurement Instrument

The questionnaire measured four latent constructs using 20 items (five per construct), each rated on a five-point Likert scale. Digital Capital (DC) was measured with five items assessing device and internet access, digital skill, adaptability to new tools, opportunity to develop digital competence, and confidence with technology for academic tasks, adapted from the digital capital framework of Ragnedda (2018). AI Literacy (AIL) was measured with five items assessing understanding of AI principles, awareness of how AI generates output, critical evaluation of AI-produced information, understanding of ethical implications, and the ability to identify appropriate use cases, informed by the AI literacy competency framework of Long and Magerko (2020). AI Usage for Learning (AIU) was measured with five items assessing the use of AI tools to understand difficult concepts, complete assignments, improve academic work, engage in regular use, and learn more efficiently. Educational Inequality Perception (EIP) was measured with five items capturing students' perceptions that unequal digital and AI resources translate into unequal learning opportunities and academic advantage. The complete item wording, together with the standardized factor loadings obtained from the confirmatory factor analysis, is reported in Table 4.

3.5 Common Method Bias Assessment

Because all constructs were measured via self-report at a single point in time, common method bias (CMB) was assessed prior to hypothesis testing using Harman's single-factor test (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003). An unrotated exploratory factor analysis of all 20 items produced a first factor accounting for 28.79% of total variance, well below the 50% threshold conventionally taken to indicate that a single latent factor does not account for the majority of covariance among the items. The emergence of a clean four-factor solution in the subsequent exploratory factor analysis, with no meaningful cross-loadings above .40 (Section 4.3), provides converging evidence against a single dominant method factor. Sampling adequacy for factor analysis was excellent (Kaiser-Meyer-Olkin measure = .886; Bartlett's test of sphericity $\chi^2(190) = 3005.49$, $p < .001$), together indicating that common method bias is unlikely to substantially distort the study's findings.

3.6 Data Analysis Strategy

Data analysis proceeded in four stages. First, internal consistency reliability of each construct was assessed using Cronbach's alpha in IBM SPSS. Second, Exploratory Factor Analysis (Principal Axis Factoring with Promax rotation) was conducted in SPSS to establish the underlying factor structure of the 20 items. Third, Confirmatory Factor Analysis (CFA) was conducted in IBM AMOS 26 using maximum likelihood estimation to assess the measurement model's fit, and composite reliability (CR), average variance extracted (AVE), and Heterotrait-Monotrait ratios (HTMT) were computed from the standardized CFA loadings and inter-factor correlations to evaluate convergent and discriminant validity. Fourth, Structural Equation Modelling (SEM) was conducted in AMOS to test the hypothesised serial mediation model, with

2,000 bias-corrected bootstrap resamples used to estimate standard errors and 95% confidence intervals for the direct, indirect, and total effects of Digital Capital on Educational Inequality Perception.

4. RESULTS

4.1 Reliability Analysis

Internal consistency reliability for each of the four constructs was assessed using Cronbach's alpha. As shown in Table 2, all four constructs exceeded the commonly recommended threshold of .70 (Hair et al., 2019), with values ranging from .803 (Digital Capital) to .846 (Educational Inequality Perception), indicating good internal consistency across the measurement instrument.

Table 2
Cronbach's Alpha Reliability for Study Constructs

Construct	No. of Items	Cronbach's α
Digital Capital (DC)	5	.803
AI Literacy (AIL)	5	.826
AI Usage for Learning (AIU)	5	.811
Educational Inequality Perception (EIP)	5	.846

Note. N = 410. α = Cronbach's alpha. All values exceed the .70 threshold recommended by Hair et al. (2019).

4.2 Exploratory Factor Analysis

Prior to confirmatory testing, an Exploratory Factor Analysis (Principal Axis Factoring, Promax rotation with Kaiser normalization) was conducted on all 20 items. Sampling adequacy was excellent (Kaiser-Meyer-Olkin measure = .886) and Bartlett's test of sphericity was significant ($\chi^2(190) = 3005.49$, $p < .001$), confirming that the correlation matrix was suitable for factor analysis. Four factors with eigenvalues greater than 1 were extracted (initial eigenvalues = 5.76, 2.90, 1.76, and 1.36), jointly accounting for 48.77% of total variance after extraction. As shown in Table 3, the Promax-rotated pattern matrix produced a clean four-factor solution: every item loaded on its intended factor at .59 or above, with no cross-loadings exceeding .40 on any other factor, providing preliminary evidence of convergent and discriminant validity ahead of confirmatory testing. Inter-factor correlations at the exploratory stage ranged from .11 to .55, broadly consistent in direction and magnitude with the confirmatory factor correlations reported in Section 4.4.

Table 3
Exploratory Factor Analysis: Pattern Matrix (Principal Axis Factoring, Promax Rotation)

Item	EIP	AIL	DC	AIU
EIP5	.791			
EIP3	.759			
EIP1	.704			

Item	EIP	AIL	DC	AIU
EIP2	.697			
EIP4	.658			
AIL5		.772		
AIL3		.729		
AIL1		.688		
AIL2		.659		
AIL4		.605		
DC5			.744	
DC3			.687	
DC2			.669	
DC4			.636	
DC1			.587	
AIU5				.720
AIU1				.708
AIU2				.640
AIU3				.636
AIU4				.631

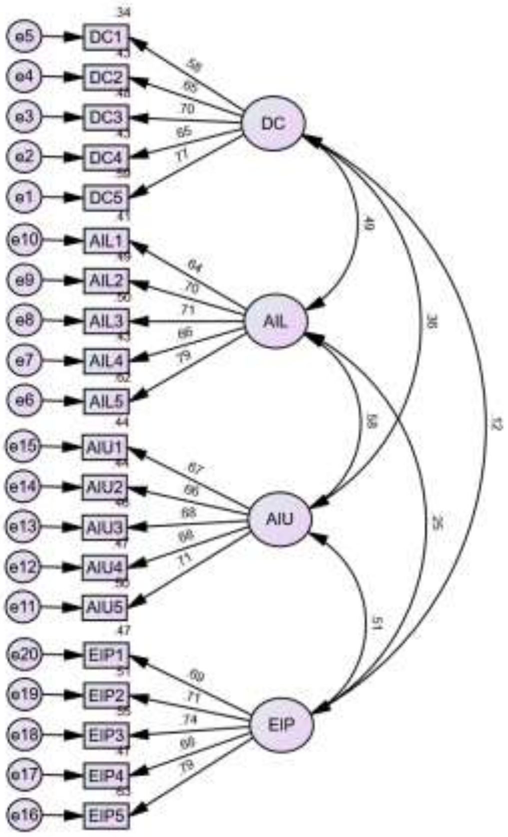
Note. Extraction method: Principal Axis Factoring. Rotation method: Promax with Kaiser Normalization, converged in 6 iterations. Loadings below .40 suppressed. KMO = .886; Bartlett's $\chi^2(190) = 3005.49$, $p < .001$. Cumulative variance extracted = 48.77%.

4.3 Confirmatory Factor Analysis

The four-factor measurement model was estimated in AMOS 26 using maximum likelihood estimation. The model produced good fit to the data: $\chi^2(164) = 211.95$, $p = .007$, $\chi^2/df = 1.29$; CFI = .983; TLI = .981; NFI = .931; GFI = .952; AGFI = .938; RMSEA = .027, 90% CI [.015, .037], PCLOSE = 1.000. Although the chi-square statistic itself was significant, this is unsurprising given its well-documented sensitivity to sample size (N = 410; Hu & Bentler, 1999); the relative chi-square (< 2), together with CFI and TLI values well above the .95 threshold and an RMSEA below .05 with a PCLOSE of 1.000, collectively indicate excellent model fit. All standardized factor loadings were positive, statistically significant ($p < .001$), and exceeded the recommended minimum of .50 (Hair et al., 2019), ranging from .580 to .791. Figure 1 presents the CFA path diagram with standardized loadings and squared multiple correlations.

Figure 1

Confirmatory Factor Analysis (CFA) Model with Standardized Factor Loadings and Inter-Factor Correlations



Note. DC = Digital Capital; AIL = AI Literacy; AIU = AI Usage for Learning; EIP = Educational Inequality Perception. Numbers on indicator arrows are standardized factor loadings; numbers near indicator boxes are squared multiple correlations (R^2). Curved double-headed arrows represent inter-factor correlations. All loadings significant at $p < .001$. Model fit: $\chi^2(164) = 211.95$, $p = .007$; CFI = .983; RMSEA = .027.

Table 4

CFA Standardized Factor Loadings, Composite Reliability, and Average Variance Extracted

Construct	Item	Item Description	λ	CR	AVE
Digital Capital (DC)	DC1	Reliable access to internet-enabled devices for academic purposes	.580		
	DC2	Adequate digital skills to use emerging technologies	.655		
	DC3	Can easily learn and adapt to new digital tools	.696		
	DC4	Sufficient opportunities to develop digital competencies	.653		

Construct	Item	Item Description	λ	CR	AVE
	DC5	Confident using technology for complex academic tasks	.765	.804	.452
AI Literacy (AIL)	AIL1	Understands the basic principles of artificial intelligence	.641		
	AIL2	Knows how AI tools generate responses or recommendations	.699		
	AIL3	Can critically evaluate information produced by AI systems	.708		
	AIL4	Understands the ethical implications of AI use	.657		
	AIL5	Can identify appropriate situations for using AI in learning	.786	.827	.490
AI Usage for Learning (AIU)	AIU1	Uses AI tools to understand difficult concepts	.665		
	AIU2	Uses AI tools to assist with assignments and projects	.665		
	AIU3	AI tools help improve the quality of academic work	.679		
	AIU4	Regularly uses AI applications for learning purposes	.683		
	AIU5	AI tools help learn more efficiently	.709	.812	.463
Educational Inequality Perception (EIP)	EIP1	Students with better digital resources benefit more from AI	.687		
	EIP2	Unequal access to technology creates differences in learning opportunities	.714		
	EIP3	AI tools may widen educational gaps among students	.742		
	EIP4	Disadvantaged students face barriers in using AI technologies	.684		
	EIP5	Access to AI resources influences academic success	.791	.846	.525

Note. λ = standardized factor loading (all significant at $p < .001$). CR = Composite Reliability. AVE = Average Variance Extracted. CR and AVE are reported once per construct, alongside its final (reference) item.

4.4 Reliability and Validity: Composite Reliability, AVE, and Discriminant Validity

Composite Reliability (CR) and Average Variance Extracted (AVE) were calculated from the standardized

CFA loadings reported in Table 4, using CR = $(\Sigma\lambda)^2 / [(\Sigma\lambda)^2 + \Sigma(1 - \lambda^2)]$ and AVE = $\Sigma\lambda^2 / n$. Composite Reliability exceeded the recommended .70 threshold for every construct, ranging from .804 (Digital Capital) to .846 (Educational Inequality Perception), confirming strong internal consistency at the construct level. AVE exceeded the conventional .50 threshold for Educational Inequality Perception (.525) but fell marginally below it for Digital Capital (.452), AI Literacy (.490), and AI Usage for Learning (.463). Because AVE is a comparatively conservative and stringent criterion, Fornell and Larcker (1981) note that convergent validity can still be considered adequate when CR exceeds .60 even where AVE falls below .50, since CR is less sensitive to the number of indicators and to modest cross-item variability than AVE. Given that CR for all four constructs comfortably exceeded this benchmark, and that all standardized loadings were significant, of acceptable magnitude, and consistent with the clean structure already observed in the EFA, convergent validity was judged adequate overall, though the modest AVE values indicate that a modest share of item variance was not attributable to the underlying constructs and may warrant refinement of the Digital Capital, AI Literacy, and AI Usage items in future scale-development work.

Discriminant validity was assessed using two complementary criteria. First, under the Fornell–Larcker (1981) criterion, the square root of each construct's AVE should exceed its correlation with every other construct. As shown in Table 5, the square root of AVE for each construct (DC = .673; AIL = .700; AIU = .680; EIP = .725) exceeded that construct's correlations with all other constructs, satisfying the Fornell–Larcker criterion in every case. Second, Heterotrait-Monotrait ratios (HTMT; Henseler, Ringle, & Sarstedt, 2015) were computed from the AMOS model-implied indicator correlation matrix. All HTMT values were well below both the conservative .85 threshold and the more liberal .90 threshold, ranging from .120 (DC–EIP) to .577 (AIL–AIU), confirming that all four constructs are empirically distinct. Because the HTMT values reported here were derived from the model-implied (rather than raw sample) indicator correlation matrix, they closely track — and in this instance are numerically very close to — the disattenuated CFA factor correlations reported in the upper section of Table 5; both indices nonetheless converge on the same conclusion of strong discriminant validity.

Table 5
Inter-Construct Correlations and HTMT Discriminant Validity Ratios

Construct	**DC**	**AIL**	**AIU**	**EIP**
Digital Capital (DC)	(.673)			
AI Literacy (AIL)	.492	(.700)		
AI Usage for Learning (AIU)	.359	.577	(.680)	
Educational Inequality Perception (EIP)	.120	.245	.512	(.725)
HTMT: DC	—			
HTMT: AIL	.493	—		
HTMT: AIU	.359	.577	—	
HTMT: EIP	.120	.245	.512	—

Note. Upper section: latent factor correlations from CFA, with the square root of AVE shown on the diagonal in parentheses (Fornell–Larcker criterion: diagonal values exceed all off-diagonal correlations in their row/column). Lower section: Heterotrait-Monotrait (HTMT) ratios. All HTMT values are below the .85/.90 thresholds (Henseler et al., 2015), confirming discriminant validity. All correlations significant at $p < .001$ except DC–EIP ($p = .046$).

Table 6
HTMT Ratio Summary for Discriminant Validity

Construct Pair	HTMT Ratio	Threshold	Decision
AIL – AIU	0.577	< 0.90	Confirmed
AIU – EIP	0.512	< 0.90	Confirmed
DC – AIL	0.493	< 0.90	Confirmed
DC – AIU	0.359	< 0.90	Confirmed
AIL – EIP	0.245	< 0.90	Confirmed
DC – EIP	0.120	< 0.90	Confirmed

Note. HTMT = Heterotrait-Monotrait ratio, computed from the AMOS model-implied indicator correlation matrix following Henseler et al. (2015). All values fall well below the conservative .85 threshold, confirming discriminant validity between every pair of constructs.

4.5 Structural Model: Path Analysis and Hypothesis Testing

The hypothesised structural model — Digital Capital → AI Literacy → AI Usage for Learning → Educational Inequality Perception, with an additional direct path from Digital Capital to Educational Inequality Perception — was estimated in AMOS 26 using maximum likelihood estimation with 2,000 bias-corrected bootstrap resamples. The structural model produced good fit to the data: $\chi^2(166) = 214.78$, $p = .006$, $\chi^2/df = 1.29$; CFI = .983; TLI = .981; NFI = .930; GFI = .951; RMSEA = .027, 90% CI [.015, .037], PCLOSE = 1.000 — fit statistics that are, as shown in Table 7, virtually identical to those of the measurement model. A chi-square difference test comparing the structural model to the freely-correlated measurement model was non-significant, $\Delta\chi^2(2) = 2.84$, $p > .05$, confirming that imposing the hypothesised directional structure did not significantly worsen fit relative to the saturated covariance structure, and that the directional (mediation) model is an adequate representation of the relationships among the four constructs. Figure 2 presents the full structural model with standardized path coefficients.

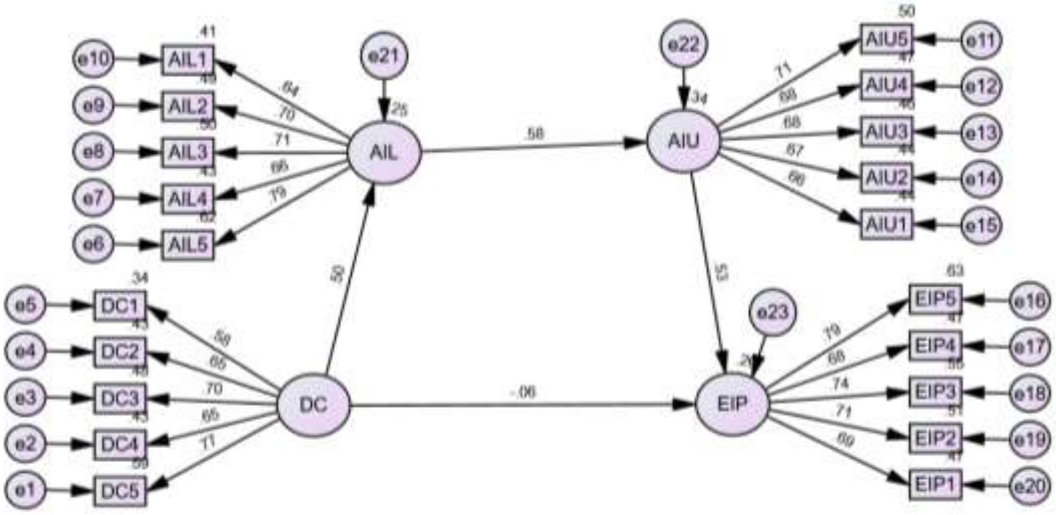
Table 7
Model Fit Indices for the CFA (Measurement) and SEM (Structural) Models

Model	χ^2	df	χ^2/df	CFI	TLI	NFI	GFI	RMSEA
CFA (Measurement) Model	211.95	164	1.29	.983	.981	.931	.952	.027
SEM (Structural) Model	214.78	166	1.29	.983	.981	.930	.951	.027

Model	χ²	df	χ²/df	CFI	TLI	NFI	GFI	RMSEA
Recommended threshold	—	—	< 3	> .95	> .95	> .95	> .95	< .08

Note. CFI = Comparative Fit Index; TLI = Tucker-Lewis Index; NFI = Normed Fit Index; GFI = Goodness of Fit Index; RMSEA = Root Mean Square Error of Approximation (90% CI [.015, .037] for both models; PCLOSE = 1.000). $\Delta\chi^2(2) = 2.84$, $p > .05$ (ns), indicating the structural model fits no worse than the saturated measurement model.

Figure 2
Structural Equation Model (SEM) Depicting Serial Mediation of AI Literacy and AI Usage between Digital Capital and Educational Inequality Perception



Note. Standardized path coefficients shown on structural paths. Numbers near indicator arrows are standardized factor loadings; numbers near latent variables are squared multiple correlations (R^2). The direct path DC → EIP ($\beta = -.06$, $p = .265$) is non-significant, indicating full mediation via AIL and AIU. DC = Digital Capital; AIL = AI Literacy; AIU = AI Usage for Learning; EIP = Educational Inequality Perception. ***$p < .001$.

Digital Capital significantly and positively predicted AI Literacy ($\beta = .502$, SE = .049, $p < .001$), supporting H1 and explaining 25.2% of the variance in AI Literacy ($R^2 = .252$). AI Literacy, in turn, significantly and positively predicted AI Usage for Learning ($\beta = .581$, SE = .045, $p < .001$), supporting H2 and explaining 33.7% of its variance ($R^2 = .337$). AI Usage for Learning significantly and positively predicted Educational Inequality Perception ($\beta = .529$, SE = .052, $p < .001$), supporting H3. Together, AI Usage for Learning and the direct path from Digital Capital explained 26.4% of the variance in Educational Inequality Perception ($R^2 = .264$). The direct path from Digital Capital to Educational Inequality Perception was small, negative, and non-significant ($\beta = -.064$, SE = .058, $p = .292$; bootstrap 95% CI [-.156, .038]), so H4 was not supported.

The standardized indirect (serial mediation) effect of Digital Capital on Educational Inequality Perception through AI Literacy and AI Usage for Learning was $\beta = .154$ (SE = .028, bootstrap 95% CI [.114, .206], $p = .001$), which is significant and excludes zero, supporting H5. Because the direct effect of Digital Capital on Educational Inequality Perception was non-significant while the indirect effect through the two mediators was significant, this pattern indicates full (indirect-only) mediation (Zhao, Lynch, & Chen, 2010): Digital Capital's association with students' perceptions of AI-driven educational inequality operates almost entirely through the sequential channel of AI Literacy and AI Usage for Learning, rather than through any additional direct or unmeasured pathway. It is worth noting that the total (unmediated) effect of Digital Capital on Educational Inequality Perception was modest and only marginally significant (β = .090, p = .099), which is consistent with a suppression-like pattern in which the small negative direct effect partially offsets the positive indirect effect — underscoring that the mediated pathway, rather than the aggregate total effect, is the more informative and theoretically meaningful quantity in this model. Table 8 summarizes the path coefficients and hypothesis testing results, and Table 9 provides an overall summary.

Table 8
Structural Path Coefficients and Hypothesis Testing Results

H	Path	β	SE	p	Decision
H1	Digital Capital → AI Literacy	.502	.049	< .001	Supported
H2	AI Literacy → AI Usage for Learning	.581	.045	< .001	Supported
H3	AI Usage for Learning → Educ. Inequality Perception	.529	.052	< .001	Supported
H4	Digital Capital → Educ. Inequality Perception (direct)	-.064	.058	.292	Not Supported
H5	DC → AIL → AIU → EIP (indirect / serial mediation)	.154	.028	.001	Supported
—	Digital Capital → Educ. Inequality Perception (total effect)	.090	—	.099	Marginal / ns

Note. β = standardized coefficient. SE = bootstrap standard error (2,000 bias-corrected bootstrap resamples). p-values for H1–H3 from the maximum likelihood critical ratio test; p-values for H4 and H5 from bias-corrected bootstrap percentile confidence intervals. 95% CI for the indirect effect (H5): [.114, .206].

Table 9
Summary of Hypothesis Testing Results

H	Hypothesis Statement	Result	Decision
H1	Digital Capital → AI Literacy (positive)	$\beta = .502, p < .001$	Supported
H2	AI Literacy → AI Usage for Learning (positive)	$\beta = .581, p < .001$	Supported
H3	AI Usage for Learning → Educational Inequality Perception (positive)	$\beta = .529, p < .001$	Supported
H4	Digital Capital → Educational Inequality Perception (direct, positive)	$\beta = -.064, p = .292$	Not Supported

H	Hypothesis Statement	Result	Decision
H5	AIL and AIU sequentially mediate DC → EIP	β = .154, 95% CI [.114, .206]	Supported (full mediation)

Note. DC = Digital Capital; AIL = AI Literacy; AIU = AI Usage for Learning; EIP = Educational Inequality Perception. H1–H3 and H5 supported at $p < .01$; H4 not supported, consistent with full (indirect-only) mediation.

5. DISCUSSION

5.1 Overview of Findings

This study examined how digital capital shapes university students' AI literacy, AI usage for learning, and perceptions of educational inequality, drawing on Bourdieu's (1986) theory of capital and reproduction and Ragnedda's (2018) digital capital theory. Four of five hypotheses were fully supported. Digital Capital significantly increased AI Literacy (H1), which in turn significantly increased AI Usage for Learning (H2), which significantly increased Educational Inequality Perception (H3). Digital Capital did not exert a significant direct effect on Educational Inequality Perception once AI Literacy and AI Usage were accounted for (H4 not supported); instead, its influence operated entirely through the sequential AI Literacy–AI Usage pathway, which was confirmed as a significant, full mediating mechanism (H5 supported).

5.2 Digital Capital as an Antecedent of AI Literacy

The strong, significant path from Digital Capital to AI Literacy ($\beta = .502$, $p < .001$) reinforces the Bourdieusian premise that digital capital functions as a foundational resource from which more specialised competencies are built (Ragnedda, 2018; Ragnedda & Ruiu, 2020). Just as van Dijk's (2005, 2020) resources and appropriation model positions digital skills as contingent on prior motivational and material access, the present findings suggest that AI-specific literacy does not emerge independently of students' broader digital resource base. In the Indian context, where government data document a substantial rural-urban gap in school-level internet and computer access (Government of India, Ministry of Education, 2024) and where national inequality reporting shows rural internet usage running more than 30 percentage points behind urban usage (Oxfam India, 2022), this pathway is likely to be a consequential channel through which broader socio-economic and geographic disparities are converted into disparities in AI-related competence among university students.

5.3 The AI Literacy–Usage–Inequality Pathway

The significant path from AI Literacy to AI Usage for Learning ($\beta = .581$, $p < .001$) is consistent with the broader digital-skills literature showing that competence is a strong proximal driver of sustained technology use (van Deursen & van Dijk, 2014). More striking is the significant path from AI Usage for Learning to Educational Inequality Perception ($\beta = .529$, $p < .001$): students who use AI tools more extensively for learning are also more likely to perceive that AI is contributing to unequal educational opportunity. This is consistent with recent evidence that generative AI adoption in higher education is itself unevenly distributed and is increasingly described as a distinct "digital AI divide" (EDUCAUSE, 2025; Beckman et al., 2025), and it suggests that heavier AI users are not merely benefiting from AI in isolation — they are simultaneously the students best positioned to observe, and be concerned about, the resource and skill preconditions that made their own AI usage possible in the first place.

5.4 Full Mediation and the Limits of Direct Access

Perhaps the most theoretically important finding is the pattern of full, indirect-only mediation (Zhao et al., 2010) in the Digital Capital–Educational Inequality Perception relationship: the direct path was small, negative, and non-significant ($\beta = -.064$, $p = .292$), while the indirect path through AI Literacy and AI Usage was significant and precisely estimated ($\beta = .154$, 95% CI [.114, .206], $p = .001$). In practical terms, this means that simply possessing digital resources and access — Digital Capital in isolation — was not sufficient to shape students' perceptions of educational inequality; it was the conversion of that capital into AI literacy, and subsequently into sustained AI usage, that carried the effect. This is precisely the sequential conversion process that Bourdieu's (1986) reproduction theory anticipates: capital reproduces advantage not automatically, but through successive, skill-mediated conversion into further capital and, ultimately, into perceived and real advantage. For policy and practice, this finding implies that closing the access gap (providing devices and connectivity) alone is unlikely to be sufficient; without parallel investment in AI literacy instruction, unequal access will continue to be converted into unequal AI usage and, in turn, into a widening perceived and actual achievement gap.

5.5 Theoretical Contributions

This study extends Bourdieu's (1986) theory of capital and reproduction, together with Ragnedda's (2018) digital capital framework, into the domain of artificial intelligence in higher education, offering one of the first empirically tested serial mediation models linking digital capital to AI literacy, AI usage, and perceived educational inequality in an Indian university setting. By demonstrating that digital capital's influence on perceived inequality is fully carried by the AI literacy–usage pathway rather than operating directly, the study provides empirical support for treating AI literacy as a distinct, theoretically consequential link in the digital divide's "successive layers" model (van Dijk, 2005, 2020) — a link that sits between general digital capital and technology-specific usage outcomes and that has received comparatively little empirical attention in the SEM-based digital divide literature to date.

6. CONCLUSION

6.1 Summary of Findings

This study provided robust empirical evidence, based on a survey of 410 Indian university students, that digital capital shapes students' perceptions of AI-driven educational inequality primarily through a sequential pathway of AI literacy and AI usage for learning, rather than through a direct, unmediated channel. Digital Capital significantly predicted AI Literacy, which significantly predicted AI Usage for Learning, which significantly predicted Educational Inequality Perception, and the overall indirect (serial mediation) pathway was significant and fully accounted for Digital Capital's association with perceived inequality.

6.2 Practical Implications

Several practical implications follow. First, higher education institutions and policymakers implementing India's National Education Policy 2020 digital-learning agenda (Government of India, Ministry of Education, 2020) should recognise that expanding device and connectivity access (digital capital) is a necessary but not sufficient condition for equitable AI integration; targeted AI literacy instruction is required to ensure that access translates into effective, critical AI usage rather than being left unconverted. Second, universities should embed AI literacy — covering basic AI concepts, critical evaluation of AI-generated content, and awareness of ethical implications (Long & Magerko, 2020) — directly into undergraduate curricula rather than treating it as an optional or extracurricular skill. Third, institutions serving predominantly rural or lower-income student populations, where digital capital is likely to be most constrained (Oxfam India, 2022), should be prioritised for device-lending, connectivity-subsidy, and AI-literacy training programmes. Fourth, given that heavier AI users are also more likely to perceive AI as widening educational gaps, institutions should proactively monitor and address disparities in AI adoption across student sub-groups rather than assuming that rising overall AI usage is uniformly beneficial.

6.3 Limitations and Future Directions

Several limitations should be acknowledged. The cross-sectional design precludes strong causal inference regarding the direction of the hypothesised relationships; longitudinal or experimental designs would strengthen causal claims about how digital capital shapes AI literacy and usage over time. The reliance on self-report measures introduces potential social desirability and common method bias, although Harman's single-factor test and the clean four-factor EFA/CFA structure suggest this risk was limited in the present data. The sample, while adequate for SEM, was not drawn using probability sampling and was concentrated in a subset of undergraduate courses and institution types, which may limit generalisability to postgraduate students, other disciplines, or other Indian states. The modest AVE values for three of the four constructs (though offset by acceptable composite reliability) suggest that the Digital Capital, AI Literacy, and AI Usage item sets could benefit from refinement in future scale-development work. Finally, Educational Inequality Perception, as operationalised here, captures students' subjective perceptions rather than objective, measured outcomes such as grades or degree completion; future research should combine perceptual measures with objective academic outcome data, and should examine potential moderators — such as institution type, family income, or course of study — of the digital capital–AI literacy–AI usage–inequality pathway identified in this study.

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