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Democratization or Digital Enclosure? Socio-Economic Disparities in Access to AI and Digital Learning Tools in Higher Education

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ABSTRACT

Generative Artificial Intelligence (GenAI) is widely heralded as an equalizer in higher education, yet emerging evidence suggests that tiered monetization and computational requirements may reproduce existing inequalities. Anchored in Pierre Bourdieu's theory of cultural capital and Jan van Dijk's digital divide framework, this study investigates socio-economic disparities in student adoption of GenAI tools. Utilizing a cross-sectional survey of university students (N=450) across public and private institutions, bivariate and hierarchical regression analyses were conducted. Findings indicate significant institutional ($\chi^2 = 44.18, p < .001$) and income-based ($\chi^2 = 68.92, p < .001$) divides in access to premium AI tiers. Furthermore, "Digital Cultural Capital" (prompt literacy and critical auditing) and paid subscription access independently predicted significant variance in academic self-efficacy ($\Delta R^2 = .234, p < .001$). The study concludes that paywalled algorithmic tools risk instituting a modern digital enclosure, necessitating policy interventions such as institutional licensing consortia and standardized prompt literacy curricula.

Keywords: Digital Divide, Generative AI, EdTech, Cultural Capital, Academic Stratification, Higher Education

Higher education is undergoing an algorithmic transition. As institutions evolve beyond traditional Learning Management Systems (LMS) like Moodle and Blackboard, students increasingly rely on Generative Artificial Intelligence (GenAI) for literature synthesis, coding support, and automated tutoring (Dwivedi et al., 2023; Selwyn, 2016). While popular techno-optimism frames GenAI as a universal tutor capable of leveling historical socio-economic deficits, critical educational

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sociology cautions that technological adoption rarely occurs on a neutral terrain (Williamson et al., 2023).

The modern AI landscape is increasingly monetized through tiered subscription models, restricted API quotas, and high computational demands. This structure risks establishing what media theorists term a digital enclosure (Andrejevic, 2007), where advanced cognitive tools become paywalled private assets rather than universal learning commons.

To examine this dynamic, two frameworks are synthesized:

1. **Jan van Dijk's Resources and Appropriation Theory (2020):** Digital inequality evolves across physical/material access, skills access, and usage outcomes. In generative learning environments, this divide translates into disparities in hardware capabilities, free versus paid subscriptions, and strategic academic deployment.
2. **Pierre Bourdieu's Theory of Capital (1986):** Economic capital directly secures objectified digital assets (premium subscriptions, high-end hardware). These are activated via embodied digital cultural capital, namely prompt literacy, critical heuristic evaluation, and syntactic fluency, which subsequently yields institutionalized academic advantages and elevated academic self-efficacy (Calderón Gómez, 2021).

Research Questions

- RQ1: Are there significant disparities in access to premium AI tools between public and private university students and across household income tiers?
- RQ2: How does a student's socio-economic status influence their digital cultural capital (prompt literacy)?
- RQ3: Does unequal access to advanced AI tools independently predict variations in academic self-efficacy?

METHODOLOGY

Design & Sample

A cross-sectional quantitative survey was conducted across higher education institutions. Using stratified multistage sampling, participants (N = 450) were recruited across:

- **Institutional Type:** Public/State-funded (n = 235, 52.2%) and Private/Deemed universities (n = 215, 47.8%).
- **Discipline:** STEM (53.3%) and Non-STEM (46.7%).

Power analysis using G Power 3.1 confirmed that N=450 provides sufficient power (>0.95 , $\alpha = .05$) to detect small-to-medium effect sizes in multivariate regression.

Measures

- **Socio-Economic Predictors:** Monthly household income quartiles (Q1 lowest to Q4 highest), parental educational attainment, institutional typology (Public vs. Private), and primary hardware profile (Smartphone-dependent vs. Dedicated personal laptop).
- **AI Access Tier:** Categorized as Non-user, Free-tier user (standard latency/token limits), or Paid/Premium subscriber.
- **Digital Cultural Capital (Prompt Literacy):** A 5-item scale ($\alpha=.84$) assessing self-rated competency in prompt structuring, iterative refinement, and hallucination verification (1 = Strongly Disagree to 5 = Strongly Agree).
- **Academic Self-Efficacy (ASE):** A 6-item validated scale ($\alpha=.86$) adapted from PALS (Midgley et al., 2000) measuring perceived academic confidence and scholastic problem-solving.

Analytical Sequence

Data were analyzed via IBM SPSS Statistics (v. 28.0) utilizing Pearson's chi-square (χ^2), one-way ANOVA with Tukey's HSD post-hoc tests, and hierarchical multiple linear regression.

EMPIRICAL RESULTS

Material and Subscription Divide

Bivariate cross-tabulations demonstrated significant structural stratification across institutional and income categories.

Table 1

Distribution Across AI Access Tiers (N=450)

Category	Free-Tier Only n (%)	Paid/Premium n (%)	Non-User n (%)	χ^2 (df)	p-value
Institutional Type				44.18 (2)	< .001
Public / State HEIs	168 (71.5%)	29 (12.3%)	38 (16.2%)		
Private HEIs	118 (54.9%)	86 (40.0%)	11 (5.1%)		
Income Quartile				68.92 (6)	< .001
Q1 (Lowest SES)	74 (68.5%)	8 (7.4%)	26 (24.1%)		
Q2 (Lower-Middle)	88 (74.6%)	16 (13.5%)	14 (11.9%)		
Q3 (Upper-Middle)	78 (67.8%)	30 (26.1%)	7 (6.1%)		
Q4 (Highest SES)	46 (42.2%)	61 (56.0%)	2 (1.8%)		

As shown in Table 1, private university students were more than three times as likely to access premium AI tools (40.0%) compared to public university students (12.3%). Similarly, premium tool ownership rose progressively from 7.4% in Q1 to 56.0% in Q4.

Stratification in Digital Cultural Capital

A one-way ANOVA tested differences in Digital Cultural Capital across income quartiles. The omnibus test was statistically significant:

$$F(3,446) = 118.26, \quad p < .001, \quad \text{Partial } \eta^2 = .443$$

- Q1 (Lowest SES): M=2.41, SD = 0.62
- Q2 (Lower-Middle): M=2.88, SD = 0.58
- Q3 (Upper-Middle): M=3.35, SD = 0.64
- Q4 (Highest SES): M=3.92, SD = 0.57

Tukey's HSD post-hoc tests confirmed that all pairwise comparisons were significant ($p < .001$), illustrating that prompting and algorithmic competencies are strongly aligned with class background.

Predictors of Academic Self-Efficacy

A three-stage hierarchical regression evaluated predictors of Academic Self-Efficacy (ASE).

Table 2
Hierarchical Multiple Regression Model Summary for Academic Self-Efficacy

Model	Predictors Added	Standardized β	t	p	R ²	ΔR^2	Sig. ΔF
1	Age, Gender, Year of Study, Discipline	—	—	—	.033	.033	.005
2	Institutional Type (1 = Private)	.158	3.29	.001	.199	.166	< .001
	Household Income Index	.219	4.42	< .001			
	Dedicated Laptop (Hardware)	.174	3.68	< .001			
3	Paid Subscription Tier	.208	4.52	< .001	.433	.234	< .001
	Digital Cultural Capital (Prompt Literacy)	.382	8.29	< .001			
	Frequency of Academic AI Use	.126	2.88	.004			

Note: Final Model $F(11,438) = 30.43, p < .001$. Collinearity diagnostics confirmed all $VIF < 1.7$.

Adding algorithmic appropriation constructs in Model 3 accounted for an additional 23.4% of variance ($\Delta R^2 = .234$). Digital cultural capital ($\beta = .382$) and paid subscription access ($\beta = .208$) emerged as the most potent unique predictors of academic self-efficacy.

DISCUSSION

The empirical findings contradict techno-determinist claims of frictionless democratization.

- 1. Hardware and Tiered Enclosure:** Aligning with van Dijk (2020), digital exclusion has migrated from basic connectivity to hardware configuration and subscription tiers. While mobile smartphones provide rudimentary access, they restrict complex academic workflows, multi-document cross-referencing, and programming tasks. Simultaneously, premium subscriptions grant privileged students access to larger context windows, multimodal tools, and superior analytical reasoning, while free-tier users face latency throttling and parameter caps.
- 2. Habitus and Algorithmic Capital Conversion:** In Bourdieu's terms, prompt literacy functions as an embodied disposition (habitus). Students from affluent domestic backgrounds demonstrate higher fluency in decomposing academic queries, contextual prompting, and critically auditing AI hallucinations. When paired with objectified economic resources (paid tools), this disposition rapidly converts into elevated academic self-efficacy and superior scholastic outputs.

Rather than bridging the divide, unmediated generative AI adoption acts as a cumulative advantage mechanism (the Matthew Effect), reinforcing academic stratification under the guise of individual merit.

POLICY RECOMMENDATIONS & CONCLUSION

Policy Interventions

- Consortia-Led Enterprise Licensing:** State higher education councils and agencies (analogous to INFLIBNET consortia) should negotiate subsidized institutional AI licenses for public universities, ensuring that cutting-edge analytical tools are treated as public educational goods.
- National Educational Technology Forum (NETF) Alignment:** Under India's National Education Policy (NEP 2020), hardware equity programs must prioritize dedicated computing devices over smartphone-only connectivity to prevent infrastructural bottlenecks.

- **Formal Prompt Literacy Curriculum:** Universities must integrate prompt architecture, hallucination auditing, and ethical attribution into compulsory undergraduate foundation courses, democratizing algorithmic capital for first-generation learners.

CONCLUSION

Generative AI tools cannot democratize higher education within an unequal material reality. Without structural interventions, the commodification of artificial intelligence will continue to enclose cognitive advantages behind economic paywalls. Achieving true educational equity requires universal institutional licensing, hardware parity, and formal digital cultural literacy across the post-secondary landscape.

REFERENCES

- Andrejevic, M. (2007). Surveillance in the digital enclosure. *The Communication Review*, 10(4), 295–317. <https://doi.org/10.1080/10714420701715365>
- Bourdieu, P. (1986). The forms of capital. In J. G. Richardson (Ed.), *Handbook of Theory and Research for the Sociology of Education* (pp. 241–258). Greenwood Press.
- Calderón Gómez, C. (2021). The digital divide revisited: Cultural capital and digital inequality in higher education. *Information, Communication & Society*, 24(12), 1774–1791. <https://doi.org/10.1080/1369118X.2020.1731582>
- Dwivedi, Y. K., Kshetri, N., Hughes, L., Slade, E. L., Jeyaraj, A., Kar, A. K., ... & Wright, R. (2023). “So what if ChatGPT wrote it?” Multidisciplinary perspectives on opportunities, challenges and implications of generative conversational AI for research, practice and policy. *International Journal of Information Management*, 71, 102642. <https://doi.org/10.1016/j.ijinfomgt.2023.102642>
- Midgley, C., Maehr, M. L., Hruda, L. Z., Anderman, E., Anderman, L., Freeman, K. E., ... & Urdan, T. (2000). *Manual for the Patterns of Adaptive Learning Scales (PALS)*. University of Michigan.
- Selwyn, N. (2016). *Is technology good for education?* Polity Press.
- van Dijk, J. A. (2020). *The digital divide*. John Wiley & Sons.
- Williamson, B., Macgilchrist, F., & Potter, J. (2023). Re-examining AI, platform capitalism, and educational futures. *Learning, Media and Technology*, 48(1), 1–5. <https://doi.org/10.1080/17439884.2023.2167830>