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The Digital Paradox in West Bengal's Higher Education: A Quantitative Analysis of Socioeconomic Determinants of Digital Exclusion and Capability

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Abstract: The recent New Education Policy (NEP) taken by India aims to promote digital learning. However, this shift to digital learning tends to reinforce old social hierarchies instead of removing them. This paper aims to analyse the socioeconomic determinants of digital inequality among selected university students in West Bengal. This paper builds its foundation on Amartya Sen's Capability Approach. It analytically focuses on simple device ownership to actual digital capabilities. The analysis is based on field survey data of 478 students. Using the multiple regression technique and mediation analysis models, the paper shows that digital capability is a main mechanism of academic success. It explains almost 42.3 per cent of the relationship between family income and academic performance. More importantly, the interaction models show a distinct Digital Paradox. It is observed that while rising family income vastly improves the digital capability of students from the general category, it has a substantially lower impact for marginalised caste (SC/ST) students. This proves that structural caste barriers strongly transcend economic class. The data also exposes severe and multiple disadvantages. Students belonging to rural locations, Muslims, and from lower castes experience the highest rates of digital exclusion. The findings of the paper show that the current government policies focusing solely on hardware distribution are empirically insufficient. To prevent technology from acting as an engine of social reproduction, educational policy must evolve from providing raw digital resources to actively building targeted, intersectional digital capabilities.

Keywords: digital divide, capability approach, higher education, intersectionality, mediation analysis, social inequality

1. Introduction

Education in the current era has witnessed a digital turning point. The growth of digitalisation in education at the university level has led to a rise in access and convenience. However, this has also risked deepening the old and existing inequalities in countries like India with various socio-economic cleavages. The onset of the COVID-19 pandemic acted as a catalyst in speeding up the technological shift to digital education around the globe. That which started as a minor innovation has become a central part of teaching, learning, and governance (Williamson et al., 2020).

In India, the implementation of the National Education Policy (NEP) 2020, which promotes a digital-first approach, has fuelled

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this change a great deal. NEP emphasises creating a digital environment by focusing on learning online, along with digital repositories and technology integration. These are expected to act as keys to achieving equitable and high-quality education (Government of India, 2020). Yet, behind this talk of equality is a persistent and troubling paradox. Though the digital tool has been hailed as a great equaliser in most cases, it has reinforced the existing social divides. Rather than breaking down the barriers, the abrupt shift to online education can actually strengthen existing economic hierarchies by increasing the digital divide (van de Werfhorst et al., 2022; Beaunoyer et al., 2020).

The digital paradox is particularly noticeable in the context of India. India has a longstanding structural inequality and strong social cleavages. This arises from existing social institutions of caste, class, religion, gender, and geography. These institutions have shaped both educational access and outcomes. The shift from traditional structures to digital platforms has not happened under equitable conditions. Oxfam India (2022) in their study show that the Indian digital divide is not simply a binary division between those who have access and those who do not have it. It is rather a gamut of complex systems involving factors like quality, reliability and digital capability. Their study at the national level points out that students from marginalised communities like Scheduled Caste (SC) and Scheduled Tribe (ST) are most inequitably affected. The study points out that even after being equipped with smartphones, students from marginalised communities encounter substantially lower bandwidth along with shared device usage and limited digital literacy as compared to their General Category counterparts. The presence of such disparities directly impacts academic engagement in hybrid learning models.

The sudden transition from face-to-face class teaching to remote teaching revealed deep vulnerabilities in the preparedness of educational systems. The lack of access to devices and internet connectivity created a severe barrier for marginalised students (Means & Neisler, 2020). Furthermore, this gap is exacerbated by gendered expectations and household responsibilities (Mathrani et al., 2021)

To examine this paradox of advancement of digital education amidst the presence of strong social inequalities, the Indian state of West Bengal becomes a critical and understudied sample. The state's higher education system is shaped by a legacy of social reform and a complex socio-political environment. It includes established public universities, an expanding private sector, and an extensive affiliating college network reflecting broader national contrasts. Preliminary evidence indicates that the state's digital transformation reproduces existing social divisions. Radhakrishnan (2024), in their study on online learning adoption in Eastern India show that Muslim students in West Bengal, especially women, experience some of the highest levels of "digital anxiety" and access barriers. These problems are linked to socioeconomic marginalisation and gender-based restrictions on technology use. Data from the National Sample Survey (National Sample Survey Office [NSSO], 2020) shows that, despite moderate internet penetration, West Bengal evidences pronounced intra-state disparities in digital access. For example, districts such as Kolkata and North 24 Parganas report high rates of personal computer and broadband use, whereas districts like Purulia and Murshidabad depend predominantly on mobile data and shared devices for educational activities.

Building on the above premise, this paper aims to ask the following research questions in the context of West Bengal: (1)

What is the magnitude and structure of disparity in digital access and digital capability among university students? (2) How do intersections of socio-economic identities like caste, religion, family income, parental education, and geography impact these digital outcomes? (3) What is the relationship between digital inequality and students' perceived academic outcomes and preparedness for an AI-assisted educational future?

In order to answer these questions, we use Amartya Sen's Capability Approach as our main conceptual framework. This approach shifts the analytical focus from mere resources (devices, connectivity) to "functionings" (what students can actually do and be in the digital academic space) and the "capabilities" (the real freedoms to achieve these functionings) (Sen, 1999; Nussbaum, 2011). In our analysis, we will consider that a student's digital capability is not just determined by ownership of a laptop or smartphone; instead, we shall focus on their effective freedom. This freedom will be measured by the ability of the student in different aspects. This aspect would involve the ability to attend a stable video lecture or to submit an online assignment without anxiety. Further, the student must be able to utilise analytical software and critically assess digital sources, as well as how well the student can interact with AI software to improve their productivity. The use of this analytical framework helps us to examine the prevalence of digital paradox empirically. Such an exercise helps to analyse the failure to transform resources into esteemed academic liberties. This failure is characterised by logical patterns of socioeconomic position.

The study uses a quantitative field survey of 478 students across a stratified sample of West Bengal's diverse higher education institutions. Using this cross-sectional data, this paper aims to produce rigorous, empirical evidence on the specific nature of digital exclusion in the state. The findings will help develop an actionable and data-driven foundation for moving beyond a generic digital roadmap to a justice-oriented renewal, i.e., one that recognises that in a deeply stratified society, true digital integration must begin with the conscious removal of the very inequalities it risks generating.

2. Literature Review and Theoretical Framework

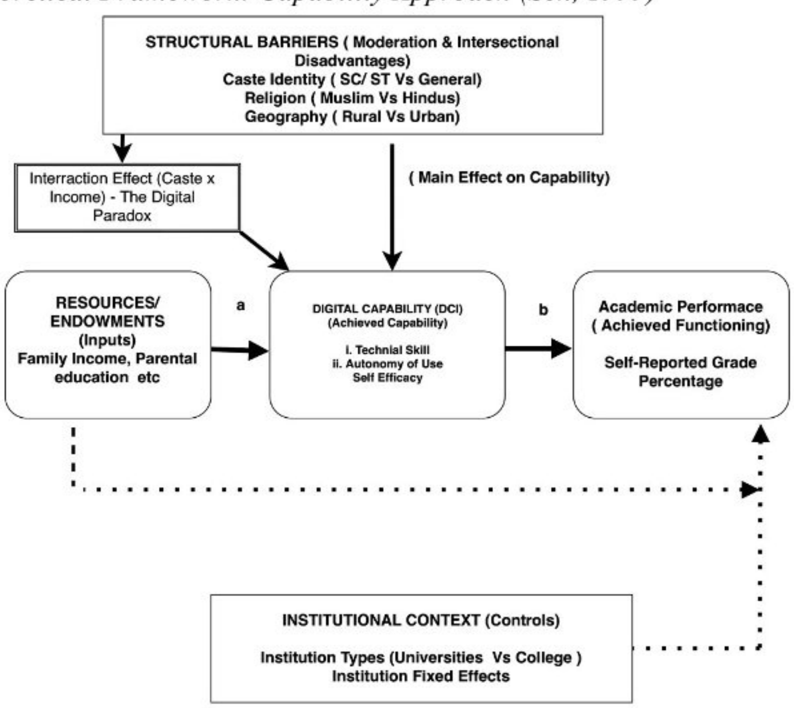
The prevalence of the digital divide in education is not just about owning a device; it is about how people use technology to learn. Recent studies show that this gap is growing in developing countries. In India, the National Education Policy 2020 pushed for digital learning. However, research proves this policy often leaves poor students behind. Banwari & Singh (2024) found that rural students face a severe lack of internet and stable electricity. This makes regular online classes nearly impossible for them. A recent report by the Children's LoveCastles Trust (2022) also shows that device ownership does not equal access. Even when rural students have smartphones at home, they rarely have exclusive access to them. A single device in a family is often shared by different family members, creating a hindrance to proper learning. Further, this sharing severely limits the time students can spend on their studies.

To understand this problem completely, we must move beyond counting laptops/ computers or smartphones. We must measure what students can actually achieve with the available technology. This study draws its theoretical motivation from Amartya Sen's Capability Approach (1999). Sen argues that human development is about freedom, and it is not just about having resources but about having the ability to convert those resources into meaningful actions. In the digital context, owning a laptop is a mere resource. Being able to use that laptop to finish a research paper or learn new software is a capability. Nussbaum (2011) expanded on this idea. She stated that social structures often restrict these capabilities. Therefore, the digital capability of a student depends heavily on their socio-economic environment.

The social environment in a developing country like India is undoubtedly divided by religion, caste, gender and location of residence (geography). The intersection of these factors generates deep-rooted social and economic inequality. This concept is known as intersectionality (Sen et al., 2009). Sehrawat & Niranjan (2024) explain that the intersection of caste and class leads to blocking socially marginalised groups from digital spaces. For example, Scheduled Caste (SC) and Scheduled Tribe (ST) students often lack the historical social capital required to build digital skills. Similarly, students from minority religious backgrounds often face unique challenges in terms of financial and social positioning. When a student hails from a rural region, is financially weak, and from a marginalised caste, they face multiple (triple) disadvantages. However, the majority of the current literature focuses on these problems in isolation and rarely measures these overlapping factors together. This study aims to fill that gap by measuring how this specific intersection affects digital capability in West Bengal.

The theoretical framework on which this paper is built is shown in Figure 1 below. The theoretical framework is built on Sen's (1999) idea of translation of commodity to functioning. By incorporating the role of endowments at the family level, the impact of socio-economic identities, the existing disadvantages, digital capabilities and controlling the institutional impact, the paper aims to capture the outcome using students' performance.

Figure 1: Theoretical Framework: Capability Approach (Sen, 1999)



Source: Author's Understanding

3. Methodology

3.1. Research Design

The quantitative analysis of this paper is based on cross-sectional data collected from a field survey. The research design tries to empirically examine the correlation between the socioeconomic status of the student, along with their digital access and competence within the higher education system of West Bengal. It should be noted that the design is explanatory and correlational. The main aim is to identify and determine the strength of specific associations between explanatory variables like caste, religion, income, geography and outcome variables like digital capability, connectivity reliability, and digital anxiety.

A cross-sectional approach is appropriate for establishing the current circumstance of the digital paradox at a particular moment, providing an essential snapshot required for guiding swift policy interventions (Creswell & Creswell, 2018). However, as we use a cross-sectional design, no causal claims are made. All reported relationships are merely associative.

3.2. Hypotheses

Based on the conceptual framework (Sen's Capability Approach) and the review of literature, the paper aims to test the following hypothesis:

- **H_1:** Digital Capability Index (DCI) scores will be significantly lower for Scheduled Caste (SC) and Scheduled Tribe (ST) students compared to General category students, controlling for income, parental education, and location constant.
- **H_2:** Muslim students will have greatly higher digital anxiety and lower DCI scores than Hindu students, after controlling for socioeconomic covariates.
- **H_3:** Rural location will be an important negative predictor of connectivity reliability and DCI, even after adjusting for income and institutional fixed effects.
- **H_4:** The positive association between family income and DCI will be far weaker for SC/ST students (interaction hypothesis).
- **H_5:** DCI will mediate a substantial proportion of the association between socioeconomic status (family income) and self-reported academic performance.

3.3. Study Population, Sampling Strategy, and Sample

The target population comprised all undergraduate and postgraduate students enrolled in higher education institutions (HEIs) across West Bengal, for the 2024-2025 academic year.

In order to ensure proper representation across critical institutional and geographical variables that can influence digital access, a stratified multistage random sampling technique was used (Teddlie & Yu, 2007).

In the first stage, the stratification was done on the basis of Institution Type and Location. The HEIs in West Bengal were stratified along two main groups. Firstly, by the type of institution, i.e., Public State University, Private University, Government/Aided College, Private College; and secondly by geographical location. This included Kolkata Metropolitan Area (KMA), Other Municipal Corporations (Siliguri, Asansol, Kalyani, etc.), and Rural/Semi-urban Districts. So, for the first stage, we have 4x3 = 12 strata.

The second stage of analysis required selection of institutions. From each stratum, one institution was randomly selected. This resulted in 12 participating institutions to ensure diversity and feasibility. The participating institutions included are University of Calcutta, Jadavpur University, Presidency University, St. Xavier's College (Kolkata), Asutosh College (Kolkata), Bidhannagar College (Kolkata), University of North Bengal (Siliguri), Kazi Nazrul University (Asansol), Kalyani University, Aliah University (Kolkata), Amity University Kolkata, and Syamsundar College (a rural constituent college of the University of Burdwan) in Bardhaman district.

In the third stage, the participants were selected from each of the 12 institutions; a target of 40 students was randomly selected from departmental enrolment rosters using a random number. The achieved sample size was 478 students with a response rate of 99.6%. This provides a margin of error of approximately ±4.5% at a 95% confidence level for population proportions.

3.3.1. Sampling Weights

As the sampling design is stratified, this led to some strata (like rural government colleges) being oversampled in comparison to their population share in order to obtain adequate statistical power. Hence, probability sampling weights were constructed so as to produce population-representative estimates.

The weight for each stratum '*s*' was calculated using the following formula:

$$W_s = \frac{N_s/N}{n_s/n}$$

Here, N_s is the estimated population size of stratum *s* (based on West Bengal Higher Education Department statistics, 2023-24). N is the total state HEI student population. 'n_s' is the sample size in stratum *s*, and n is the total sample size. All descriptive and inferential analyses incorporate these weights using the weights parameter in weighted least squares estimation (refer to Section 3.7). Unweighted sensitivity analyses were also conducted; results were directionally consistent, but weighted estimates are preferred for population inference.

3.4. Instrument Development and Measures

Using a structured, self-administered questionnaire, the data were collected. This questionnaire was developed in English and Bengali (with forward-backwards translation). It comprised four sections, designed based on a comprehensive literature review and adapted from validated instruments. The Digital Capability Scale (Ng, 2012), the Survey of Student Experiences of Remote Learning (SSERL) framework (Winstone et al., 2020), and the Digital Competence Framework for Citizens (DigComp 2.1, Vuorikari et al., 2016).

Section A: Socio-Economic and Demographic Profile

Collected data on:

- **Caste** (General, OBC, SC, ST) per Government of India categories.
- **Religion** (Hindu, Muslim, Christian, Other).
- **Annual Family Income** (in INR lakhs: <3, 3–6, 6–10, 10–20, >20; also collected as continuous for log transformation).
- **Parental Education** (highest degree attained: illiterate to postgraduate, converted to a 0–4 scale).
- **Type of Residence** (Kolkata Metro, other municipality, rural village).
- **Institution Name** and program of study.

Section B: Digital Access and Infrastructure (DAI)

Measured the *resource* aspect of Sen's framework. Variables included:

- **Primary Device for Academics** (Smartphone only, Smartphone + Laptop/PC, Only Laptop/PC).
- **Device Adequacy:** A 5-point Likert scale (1 = Highly Inadequate, 5 = Highly Adequate) rating device performance for academic tasks (e.g., "My device can run required software without lag").
- **Internet Connectivity:** Type (mobile data 4G/5G, broadband/Wi-Fi), average daily reliable connectivity hours, and a 5-point reliability scale for live classes (1 = Very Unreliable, 5 = Very Reliable).

Section C: Digital Capability Index (DCI) – Core Dependent Construct

This 20-item scale measured the *conversion factors* and achieved *functionings*. Items used a 5-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree). Sub-dimensions included:

- **Proficiency & Skills** (4 items): e.g., "I can create a multimedia presentation (e.g., PPT with embedded video) for academic purposes."
- **Academic Navigation** (4 items): e.g., "I can effectively use my university's digital library portal or online journal databases."
- **Critical Evaluation** (4 items): e.g., "I can distinguish credible academic information from misinformation on social media or websites."
- **Problem-Solving & Agency** (4 items): e.g., "I can troubleshoot common software or connectivity issues myself before seeking help."
- **AI Interaction** (4 items): e.g., "I understand how to use AI tools (like ChatGPT) responsibly to brainstorm ideas or improve my writing without plagiarising."

The DCI score was calculated as the mean of all 20 items. Internal consistency was excellent (Cronbach's $\alpha = 0.89$ in pilot, 0.91 in full sample).

Section D: Pedagogical Experience and Outcomes

- **Hybrid Learning Efficacy**: "How effective has your experience been with hybrid (mix of online and in-person) learning models?" (1 = Very Ineffective, 5 = Very Effective).
- **Digital Anxiety**: A 4-item subscale ($\alpha = 0.82$) measuring anxiety around automatic/ digital-proctored exams and automated assessment (e.g., "I worry that an automated proctoring system might wrongly flag me").
- **Self-Perceived Academic Performance**: "In comparison to your peers, how would you rate your overall academic performance?" (1 = Well Below Average, 5 = Well Above Average).

3.5. Data Collection Procedure

The data were collected from January 2025 to May 2025. The questionnaire was circulated digitally via Google Forms. A paper-based alternative was used when requested by students without reliable digital access. Institutional contacts were made via heads of the department or NSS coordinators who helped distribute a participation link along with a Participant Information Sheet detailing the purpose of the study. This helped guarantee anonymity, along with the response being voluntary in nature. Informed consent was obtained electronically (or in writing for paper surveys) at the beginning of the survey. The average completion time was 18 minutes. There were no incentives provided to the participants, but the summary of the findings was shared with those who were interested in knowing.

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3.6. Description of the Variables used in analysis

Variable Type	Variable Name	Operationalisation	Scale
Dependent (Continuous)	Digital Capability Index (DCI)	Mean of 20 Likert items	1–5
Dependent (Binary)	High DCI	DCI ≥ 3.85 (top 25%; explained in Section 3.6.1)	0/1
Dependent (Continuous)	Connectivity Reliability	Single Likert item	1–5
Independent (Continuous)	Family Income	Log-transformed annual income (Rs lakhs)	Continuous
Independent (Continuous)	Parental Education	0–4 scale (0=illiterate, 1= Primary education only, 2= Completed School education, 3= Graduate 4=postgraduate and above)	Continuous
Independent (Categorical)	Caste	Dummy variables: SC/ST (1/0), OBC (1/0)	Binary
Independent (Categorical)	Religion	Dummy: Muslim (1/0)	Binary
Independent (Categorical)	Location	Dummy: Rural (1/0)	Binary
Independent (Categorical)	Institution	Fixed effects (11 dummies with reference to University of Calcutta)	Categorical
Mediator	DCI	Same as above	Continuous
Outcome (Mediation)	Academic Performance	Single Likert item	1–5

3.6.1. Digital Capability Index (DCI) Threshold

In order to determine the threshold of Digital Capability Index (DCI), the value of DCI ≥ 3.85, which is the weighted 75th percentile, was selected. This selection is based on two important considerations. Firstly, it aligns with the proficient benchmark in validated digital literacy frameworks such as the European Digital Competence Framework for Citizens (DigComp 2.1), which defines the top quartile as highly proficient. Secondly, it represents a natural breakpoint in the weighted DCI distribution. Sensitivity analyses to ensure robustness were conducted using alternative thresholds like the 70th and 80th percentiles, etc, produced substantively identical results

3.7. Analysis of Data

All analyses were conducted using R version 4.3.2 (R Core Team, 2023) with the survey package (Lumley, 2020) for weighted estimation, the lfe package (Gaure, 2013) for linear models with high-dimensional fixed effects, and the mediation package (Tingley et al., 2014) for causal mediation analysis (with the caveat that the term "causal" is used only in the statistical sense; no true causal identification is claimed due to cross-sectional design).

3.7.1. Descriptive Statistics

Weighted means, standard errors, frequencies, and percentages were computed for all variables. Stratum-specific weights were applied using the svydesign() function.

3.7.2. Bivariate Analyses

To conduct the bivariate analysis t-tests were used (weighted, with Satterthwaite degrees of freedom) to compare means between two groups (e.g., rural vs. urban, Muslim vs. Hindu). One-way ANOVA (weighted, with design-based F-tests) was used to compare means across caste groups, followed by weighted Tukey HSD post-hoc tests. Finally, Pearson correlations (weighted) were computed between continuous variables.

3.7.3. Multivariate Regression Models

Model 1: Linear Regression Predicting DCI (Continuous)

The first model considered a weighted ordinary least squares (OLS) with institution fixed effects, which included 11 dummies with reference point to the University of Calcutta. Here the independent variable for the regression included income (in log terms), education of the parents, device adequacy, connectivity reliability, connectivity hours, rural (dummy), SC/ST (dummy), Muslim (dummy), and institution fixed effects. Unstandardised coefficients (β) were reported along with standard errors, t-statistics, p-values, and standardised coefficients (β*). We observe $R^2 = 0.612$, which is high but is plausible given inclusion of proximal predictors (connectivity, device adequacy) that directly measure digital resources, unlike typical distal socioeconomic proxies.

Model 2: Linear Regression Predicting Connectivity Reliability (Continuous)

The second model considered a weighted OLS with institution fixed effects. Here the independent variables included family income(in log form), parental education, rural, SC/ST, Muslim, and institution fixed effects.

Model 3: Logistic Regression Predicting High DCI (Binary)

The third model considered a weighted logistic regression with institution fixed effects. Here, the threshold considered was the top 25%, indicated by DCI score ≥ 3.85, whose justification is provided above. Here, the adjusted odds ratios (OR) are reported with 95% confidence intervals along with p-values, and McFadden's pseudo R^2.

Interaction Model (H_4): Weighted OLS with DCI as outcome, including centred log income, SC/ST dummy, and their product term, plus all other controls and institution fixed effects.

Mediation Analysis (H_5): The weighted mediation analysis was conducted using the product-of-coefficients method with 5,000 bootstrap resamples (Preacher & Hayes, 2008). The mediator considered was DCI, along with the independent variable considered being log income, and the outcome was academic performance. Controls included parental education, rural, SC/ST, Muslim, and institution fixed effects.

3.7.4. Institutional Fixed Effects

Institution fixed effects, measured using 11 dummy variables, were included in all regression models. This was done to ensure that all time-invariant unobserved heterogeneity across the 12 participating institutions (e.g., campus Wi-Fi quality, library digital resources, faculty digital training, administrative support) was absorbed. This approach is more rigorous than using only broad institution-type categories. In order

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to test the joint significance of fixed effects F-test (for linear models) or a likelihood-ratio test (for logistic models) was used.

3.7.5. Model Diagnostics and Assumption Checks

Jarque-Bera (JB) test was considered to check the normality of the residuals. Breusch-Pagan test (weighted version) was used to check for the presence of heteroscedasticity. The robust standard error was used to remove any possibility of heteroskedasticity. The standard Variance inflation factor (VIF) test was done to check for multicollinearity. VIF values less than 4 were considered acceptable. To check the independence of errors, the Durbin-Watson statistic was considered with a target value of 1.5 to 2.5. Finally F-test or LR test was conducted to check for the joint significance of the institution fixed effect.

3.7.6. Effect Sizes

For comparison of groups, Cohen's d (weighted, with pooled standard deviations) was considered. It is interpreted as follows: small (0.2), medium (0.5), large (0.8) per Cohen (1988). Standardised coefficients (β^*) for regression predictors were considered. Pseudo R^2 (McFadden) for logistic regression was checked.

3.8. Limitations of the study

The study at the very onset would acknowledge the limitations. Firstly, it follows a Cross-sectional design, which prevents causal inference. The associations reported (e.g., "relationship between income and DCI") are correlational. There, however, is a possibility of reverse causality. The digitally capable students may come from wealthier families, or unobserved factors like intrinsic motivation or prior digital training could confound relationships. No claims of causation are made from this analysis. Secondly, the measures are self-reported in nature**.** Note that the students provided information like their digital anxiety, their academic performance and even aspects of DCI may be subject to social desirability and recall bias. However, the DCI scale demonstrated good internal consistency (α value of 0.91), and anonymity was emphasised to reduce bias. Thirdly, the sampling weights were constructed from available population data, which may contain measurement error in stratum sizes. To minimise this, sensitivity analyses using unweighted models were conducted. It produced similar coefficient directions but different magnitudes. The weighted estimates are preferred for population inference. However, the results should be interpreted with this usual caveat. Fourthly, to absorb time-invariant heterogeneity, the study uses institutional fixed effects. Although this serves the basic purpose, it cannot control for time-varying institutional factors such as a sudden investment in digital infrastructure during the study period. Fixed effects also cannot account for selection into institutions (e.g., students self-selecting into better-resourced universities). Fifth important point to note is that the results can be used as generalisability to other Indian states, as West Bengal has a unique socio-political and educational history, like most Indian states have their own. Replication studies in other states are recommended for strengthening the findings. Finally, non-response bias could not be rigorously tested because non-respondents did not provide data. However, the response rate (99.6%) was exceptionally high, minimising this concern

4. Results

4.1. Descriptive Statistics of the Weighted Sample

Probability sampling weight is applied to account for the multistage stratified sampling design. The sample of 478 students represented the weighted analytical sample, which was estimated from an estimated population of approx. 26 lakh students in higher education in West Bengal (All India Survey on Higher Education [AISHE], 2021). Table 1 presents the weighted demographic characteristics.

Table 1. Demographic Profile of the Sample (Weighted)

Characteristic	Category	Weighted % (SE)	Unweighted N
Caste	General	28.7 (1.2)	121
	OBC	34.1 (1.4)	166
	SC	29.8 (1.3)	154
	ST	7.4 (0.8)	37
Religion	Hindu	74.2 (1.6)	343
	Muslim	23.1 (1.4)	121
	Christian	1.9 (0.4)	10
	Other	0.8 (0.3)	4
Location	Kolkata Metro	45.3 (1.8)	192
	Other Municipal	33.2 (1.6)	166
	Rural	21.5 (1.4)	120
Institution Type	Public State University	38.6 (1.7)	168
	Private University	22.4 (1.5)	95
	Government College	27.5 (1.6)	144
	Private College	11.5 (1.1)	71

(Note: The standard error (SE) in the parentheses shows the design-based standard error, which accounts for stratification and weighting.)
(Source: Author's Calculation from field data)

Table 2 reports weighted means and standard errors for the key continuous variables. The mean Digital Capability Index (DCI) score was 3.18 with a standard error of 0.034. It is measured on a scale of 1 to 5. The result indicates a moderate digital capability with substantial variation.

Table 2. Summary Statistics of Variables

Variable	Weighted Mean	SE	95% CI	Range
Digital Capability Index (DCI)	3.18	0.034	[3.11, 3.25]	1.45–4.85
Connectivity Reliability (1–5)	3.62	0.048	[3.53, 3.71]	1.20–4.90
Device Adequacy (1–5)	2.92	0.047	[2.83, 3.01]	1.00–5.00
Digital Anxiety (1–5)	3.09	0.036	[3.02, 3.16]	1.30–4.80
Self-Perceived Academic Performance (1–5)	3.45	0.031	[3.39, 3.51]	1.50–4.80
Family Income (lakhs INR)	6.14	0.192	[5.76, 6.52]	1.05–45.30
Parental Education Score (0–4)	2.52	0.041	[2.44, 2.60]	0.32–3.98

(Source: Author's Calculation from field data)

4.2. Bivariate Associations and Hypothesis Testing

4.2.1. Hypothesis 1: Caste-Based Disparities in Digital Capability

A weighted one-way analysis of covariance (ANCOVA), controlling for family income, parental education, and institution fixed effects, revealed a statistically significant association between caste and DCI, $F(3,462)= 38.24$, $p<0.001$, partial $\eta^2=0.19$. Adjusted means are presented in Table 3.

Table 3. Adjusted Mean DCI by Caste (Controlling for Income, Parental Education, and Institution FE)

Caste	Adjusted Mean DCI	SE	95% CI	Difference from General
General	3.72	0.065	[3.59, 3.85]	Reference
OBC	3.28	0.055	[3.17, 3.39]	–0.44***
SC	2.91	0.059	[2.79, 3.03]	–0.81***
ST	2.69	0.098	[2.50, 2.88]	–1.03***

*** p<0.001 (Tukey HSD-adjusted for multiple comparisons)*

Post-hoc pairwise comparisons using Tukey's HSD test indicated that all caste groups differed significantly from one another ($p<0.01$) except SC versus ST ($p=0.087$). The effect size for the contrast between General and SC/ST students was large (Cohen's $d=0.88$, 95% CI [0.68, 1.08]). Thus, H_1 is supported.

4.2.2. Hypothesis 2: Religion-Based Disparities

Weighted independent-samples t-tests compared Hindu and Muslim students on DCI and digital anxiety (Table 4). Muslim students scored significantly lower on DCI by 0.39 points (medium effect, $d=0.59$) and significantly higher on digital anxiety by 0.37 points (medium effect, $d=0.54$). Both differences were statistically significant at $p<0.001$. **H_2 is supported.**

Table 4. Religion-Based Differences in DCI and Digital Anxiety

Outcome	Hindu Mean (SE)	Muslim Mean (SE)	Difference	t	df	p	Cohen's d
DCI Score	3.28 (0.038)	2.89 (0.062)	–0.39	–5.62	182	<0.001	0.59
Digital Anxiety	3.01 (0.041)	3.38 (0.067)	+0.37	4.88	178	<0.001	0.54

4.2.3. Hypothesis 3: Rural-Urban Disparities

Weighted linear regression with institution fixed effects (Model 2 as described in Section 4.3.2) showed that rural location was associated with a significant decrease in connectivity reliability ($\beta= -0.782$, $SE=0.098$, $p<0.001$, partial $\eta^2=0.124$) and in DCI ($\beta=-0.198$, $SE=0.045$, $p<0.001$, partial $\eta^2= 0.042$), holding all other variables constant. Rural students had, on average, 0.78 points lower connectivity reliability and 0.20 points lower DCI compared to urban students. Thus, **H_3 is supported.**

4.3. Multivariate Regression Results

4.3.1. Model 1: Predicting Digital Capability Index (DCI)

A weighted linear regression with institution fixed effects was estimated to predict DCI (continuous, 1–5). The model explained a substantial proportion of variance in DCI (R^2=0.612, adjusted R^2= 0.585, F (25,452) = 28.56, *p* <0.001). The high R^2 is plausible given the inclusion of proximal predictors (connectivity reliability, device adequacy) that directly measure the resources constituting digital capability. Table 5 reports unstandardised coefficients, standard errors, and standardised coefficients.

Table 5. Weighted Linear Regression Results for DCI (Model 1)

Predictor	**β (Unstandardised)**	**SE**	**t**	**p**	**β* (Standardised)**
Intercept	0.912	0.178	5.12	<0.001	–
Log (Family Income)	0.218	0.041	5.32	<0.001	0.228
Parental Education	0.142	0.037	3.84	<0.001	0.158
Device Adequacy	0.195	0.031	6.29	<0.001	0.265
Connectivity Reliability	0.262	0.030	8.73	<0.001	0.342
Connectivity Hours (daily)	0.038	0.011	3.45	<0.001	0.128
Rural (vs. Urban)	–0.198	0.045	–4.40	<0.001	–0.162
SC/ST (vs. General/OBC)	–0.162	0.043	–3.77	<0.001	–0.152
Muslim (vs. Hindu)	–0.121	0.050	–2.42	0.016	–0.098
Institution Fixed Effects	(11 dummies; joint F = 4.23, p < 0.001)				

(Note: The standardised coefficients of β are computed from weighted estimates. Here, the Institution fixed effects are jointly significant, thus justifying their inclusion. The VIF values ranged from 1.12 to 3.45, which indicates that no multicollinearity is present.)

The strongest unique associate of DCI was connectivity reliability (β* = 0.342), followed by device adequacy (β* = 0.265) and log income (β* = 0.228). Being rural, SC/ST, or Muslim each had significant negative associations of comparable magnitude (β* between –0.10 and –0.16). These associations persist even after controlling for institutional differences via fixed effects.

4.3.2. Model 2: Predicting Connectivity Reliability

A weighted linear regression with institution fixed effects predicted connectivity reliability (1–5). Results are summarised in Table 6.

Table 6. Weighted Linear Regression Results for Connectivity Reliability (Model 2)

Predictor	**β**	**SE**	**t**	**p**	**β***
Intercept	3.124	0.215	14.53	<0.001	–
Log (Family Income)	0.168	0.044	3.82	<0.001	0.162
Parental Education	0.058	0.039	1.49	0.137	0.062
Rural (vs. Urban)	–0.782	0.098	–7.98	<0.001	–0.345
SC/ST (vs. General/OBC)	–0.132	0.047	–2.81	0.005	–0.118

Muslim (vs. Hindu)	–0.082	0.054	–1.52	0.129	–0.064
Institution Fixed Effects	(joint F = 2.98, p = 0.001)				

Note: R^2= 0.408*,* Adjusted R^2=0.382*,* F (24,453) =13.02*,* p<0.001.

The results from Table 6 above show that rural location had the largest negative association with connectivity reliability (β* = –0.345), followed by SC/ST status (β* = –0.118). Income also showed a positive association. Parental education and Muslim identity were not significant predictors of connectivity reliability after controlling for other factors.

4.3.3. Model 3: Logistic Regression Predicting High Digital Capability (Top 25%)

The threshold for high digital capability was set at DCI ≥ 3.85. This value corresponds to the weighted 75th percentile (as discussed earlier). This aligns with the available benchmark in the DigComp 2.1 framework (Vuorikari et al., 2016). Table 7 below reports the weighted prevalence of high DCI across different subgroups.

Table 7. Weighted Prevalence of High DCI by Subgroup

Subgroup	Prevalence (%)	SE
General Caste	44.2	3.1
SC/ST	16.8	2.4
Hindu	30.5	1.9
Muslim	15.2	2.8
Urban	32.8	1.7
Rural	10.4	2.2

A weighted logistic regression with institution fixed effects was estimated. The model showed good fit (McFadden's pseudo R^2=0.314 AUC = 0.842). Table 8 below presents adjusted odds ratios.

Table 8. Weighted Logistic Regression Results for High DCI (Model 3)

Predictor	Adjusted Odds Ratio (OR)	95% CI	p
Log (Family Income)	2.28	[1.72, 3.02]	<0.001
Parental Education	1.58	[1.18, 2.11]	0.002
Connectivity Reliability	1.92	[1.48, 2.49]	<0.001
Rural (vs. Urban)	0.28	[0.14, 0.56]	<0.001
SC/ST (vs. General/OBC)	0.31	[0.17, 0.57]	<0.001
Muslim (vs. Hindu)	0.45	[0.23, 0.88]	0.020

The results of Table 8 can be interpreted as follows: After taking into account the institutional fixed effects and other covariates, we observe that students from the minority community (SC/ST students) had approx. 3.23 times lower odds (1/0.31) of being in the high digital capability category in comparison to non-SC/ST students. Rural students had 3.57 times lower odds, while the Muslim students had 2.22 times lower odds**.** Factors like family income, education of parents and connectivity reliability each more than doubled the odds of high DCI.

4.4. Interaction Analysis: Caste Moderation of Income-DCI Association (H_4)

In order to test whether the positive association between family income and DCI differs by caste, a weighted linear regression model including an interaction term between log income and SC/ST status was estimated. Table 9 reports the results of the regression.

Table 9. Interaction Model for DCI (Caste × Income)

Term	β	SE	t	p	95% CI
Log Income (cantered)	0.238	0.040	5.95	<0.001	[0.159, 0.317]
SC/ST (dummy)	–0.162	0.043	–3.77	<0.001	[–0.247, –0.077]
Log Income × SC/ST	**–0.092**	**0.036**	**–2.56**	**0.011**	**[–0.163, –0.021]**

(Note: This model includes all other controls like education of parents, adequacy of device, connectivity, geographic location (rural), Religion (Muslim) and institution fixed effect)

The result of Table 9 can be interpreted as follows. The positive association between log income and DCI was significantly weaker for SC/ST students (slope = 0.238 – 0.092 = 0.146) than that for non-SC/ST students (slope = 0.238). This interaction supports the hypothesis H_4, i.e., income translates less effectively into digital capability for historically marginalised caste groups. The effect size of the interaction is small to medium (partial $\eta^2 = 0.018$), but statistically robust.

4.5. Mediation Analysis: DCI as a Mediator of the Income-Performance Association (H_5)

In order to test whether DCI mediates the association between family income and self-perceived academic performance, a weighted mediation analysis was done. The testing used bootstrapping of 5,000 resamples. All models were controlled for factors like parents' education, location, SC/ST status, Muslim status, and institution fixed effects. The result of the mediation analysis is presented in Table 10 below.

Table 10. Weighted Mediation Analysis Results (Bootstrap Resampling Technique)

Path	β (Standardised)	SE	p	95% Bootstrap CI
Total association (Impact of Income translated to Academic Performance)	0.298	0.045	<0.001	[0.210, 0.386]
Direct association (Income translation to AP, controlling for DCI)	0.172	0.048	<0.001	[0.078, 0.266]
Indirect association (Income translated to DCI translated to AP)	0.126	0.022	<0.001	[0.084, 0.171]
Proportion mediated	**42.3%**	5.8%	–	[31.5%, 54.2%]

From Table 10 above, we observe that approximately 42 per cent of the total association between family income and academic performance operated through digital capability (DCI). The indirect association was statistically significant (bootstrap CI excludes zero). This finding supports our hypothesis (**H_5**) and suggests that interventions improving digital capability could substantially reduce income-based disparities in academic outcomes.

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4.6. Summary of Hypothesis Testing Outcomes

The findings regarding each hypothesis tested are presented in Table 11.

Table 11: Summary of Hypothesis Testing

Hypothesis	Statement	Supported?	Key Evidence
H_1	SC/ST students have lower DCI than General, controlling for covariates	Yes	Adjusted mean difference = –0.81 (SC), –1.03 (ST); p < 0.001
H_2	Muslim students have lower DCI and higher digital anxiety	Yes	DCI difference = –0.39, d = 0.59; anxiety difference = +0.37, d = 0.54
H_3	Rural location negatively predicts connectivity reliability and DCI	Yes	β = –0.782 (connectivity), β = –0.198 (DCI); both p < 0.001
H_4	Income-DCI association is weaker for SC/ST students	Yes	Interaction β = –0.092, p = 0.011
H_5	DCI mediates income-academic performance association	Yes	42.3% mediated, 95% CI [31.5%, 54.2%]

4.7. Model Diagnostics and Post Estimation Checks

In order to assess the reliability of the estimates of Model 1, a series of standard diagnostic tests was performed. In order to check the normality of the residual terms, the classic Jarque-Bera (JB) test was performed. The test confirmed that the residuals were normally distributed (χ^2=4.12, p=0.127). Secondly, tests for equal variance were done using a weighted Breusch-Pagan test. The results from the test (LM=15.23, p=0.085) showed no significant evidence of heteroscedasticity at the 0.05 level. Further, the multicollinearity problem was not observed for the analysis. The maximum Variance Inflation Factor (VIF) found was 3.45 for the log income variable. For all other predictors, the VIF value remained below 3.0. The Durbin-Watson statistic was also found to be around 1.92. This falls comfortably within the acceptable 1.5 to 2.5 range. The result of the DW test confirmed the independence of the error terms. We also verified the decision to include institutional controls. The joint significance of institution fixed effects was done by the F-test. The result of the test showed that the F(11,452)=4.23 and the corresponding p <0.001. This clearly justifies the inclusion in the model. Finally, the overall fit of the logistic regression used in Model 3 was done using the Hosmer-Lemeshow test. The test result yielded a χ^2 of 8.34 with p=0.401. This indicates that the model is well chosen.

4.8. Effect Sizes for Key Disparities

To have a proper comparison between groups and the outcomes, and to have standardised effect sizes (Cohen's d), is summarised in Table 12 below.

Table 12. Cohen's d for Major Group Comparisons (Weighted)

Comparison	Outcome	Cohen's d	95% CI	Interpretation
General vs. SC/ST	DCI	0.88	[0.68, 1.08]	Large

Urban vs. Rural	DCI	0.79	[0.58, 1.00]	Large
Hindu vs. Muslim	DCI	0.59	[0.38, 0.80]	Medium
Hindu vs. Muslim	Digital Anxiety	0.54	[0.33, 0.75]	Medium

4.9. Summary of the Important Findings

The findings from the data analysis in this paper show a deep structural divide in how students access and use digital tools across West Bengal. Even after controlling for income, the education of parents, and institutional-level resources, the findings show that the marginalised caste (SC/ST) students score nearly one full point lower on the 1-to-5 Digital Capability Index (DCI) as compared to General category students. This represents a remarkably large effect size ($d=0.88$). Religious and geographic backgrounds create similar challenges. Muslim students face measurable challenges in their digital capability ($d=0.59$) while experiencing higher levels of technology-related anxiety ($d=0.54$) than their Hindu peers. Geographic location also dictates daily access. Living in a rural area directly damages connectivity reliability ($\beta = -0.345$) and reduces overall capability scores ($\beta=-0.162$). In practical terms, a rural student faces 3.6 times lower odds of reaching a high level of digital capability compared to an urban student.

The results show a few crucial hurdles beyond the isolated demographics. These hurdles arise from the existing social hierarchy, which weakens economic progress. It is found that as family income increases, it does not lead to equal improvement in digital capability for everyone. The association between income and capability is significantly weaker for marginalised students from SC/ST community. This means greater economic resources do not easily translate into digital equality across different caste groups. Importantly, this lack of digital capability directly hurts academic success. From the mediation models, it is found that the DCI explains over 40 per cent of the link between family wealth and academic performance. This suggests that targeted digital interventions could actually help narrow the broader socio-economic gaps in university classrooms.

Since the study is based on cross-sectional data, one must treat these reported associations as correlational rather than strictly causal in nature. Still, given the sheer size and consistency of these gaps across various analytical approaches, it shows us a clear reality. Aiming for renewal of digitally supported education in universities in West Bengal will be effective if the policy design explicitly acknowledges it as an intervention as a tool of social justice.

5. Discussion

The main aim of this paper was to find out how digital inequality impacts the academic outcome of students at the college/ university level in West Bengal. We found that digital capability is not just a side issue; rather, it is a major factor in how well students do in school. The mediation analysis shows a significant result that digital capability accounts for around 42 per cent of the connection between family income and academic success. This indicates that money has a significant impact on the performance of the students through the digital route. It implies that those families who have more money may end up buying more than just expensive laptops, tablets or smartphones; they can get, say, working Wi-Fi with better broadband strength. Further, they can afford a clam disturbance free places to study. Moreover, these students can also afford the time they need to learn more advanced digital skills, while the students belonging to lower-income families don't have access to these benefits. They often use older devices or shared devices, and this problem can be amplified with the trouble of data limits and broadband capacity. This lack of digital skills directly hurts their academic performance.

The most important finding is how caste and income affect each other. A lot of people who make decisions think that higher incomes will automatically close the digital divide. The finding of this study shows that this is a wrong belief. We find that a rise in income significantly improves the Digital Capability Index (DCI) for students in the General category. While the same rise in income helps SC/ST students in lesser magnitude. This is what we call the Digital Paradox, where the impact and structure of caste barriers go beyond economic class. A wealthy student who is on the outside still faces hidden punishments, where these penalties could be because of a lack of social capital in the past. They might not have friends who share digital knowledge, or they might also have to deal with subtle biases in the system. One can't buy full digital inclusion with just money.

The findings also point out that there exists a disadvantage in multiplicative form, which is created by the intersections of religion, caste and location. Those students who belong to rural regions, who are Muslim, and belong to marginalised castes face more challenges in comparison to their counterparts. The DCI scores for these students were the lowest across the sample. Important to note that the infrastructure in the rural regions of West Bengal remains inconsistent. Access to broadband is weak across different parts of Bengal. When a student combines this geographic penalty with minority religious status and lower caste, the penalty is nearly absolute. We call this triple disadvantage. While the current policies of the governments often treat all students as a uniform or homogeneous group, the results of the regression models show that they are not, and there is not one magical pill to solve the problem. The findings emphasise that this one-size-fits-all approach fails the socially weak and most vulnerable students.

The findings of this paper help to validate Amartya Sen's Capability Approach, which was the starting point of our theoretical framework. While most state governments frequently arrange the distribution of free tablets or smartphones to students, this policy treats the digital divide as a simple supply-side or resource problem. The findings of this study point out that providing a device only supplies a raw resource, but it does not automatically create a capability. To convert a tablet into academic success, a student needs a supportive environment. They need stable internet, digital literacy, and social support. Social structures act as a barrier in this conversion process for weaker marginalised groups. Therefore, unless we measure the actual capabilities, just measuring resources is useless.

5. Policy Implications

From the policymakers' point of view, the findings of this study show a need for a major shift in the approach to how one moves ahead with designing educational policies. The current initiatives by the governments mostly focus on providing the hardware. Distribution of free tablets, laptops, and smartphones is often the most popular political tool. However, the findings of the study indicate that this hardware-centric approach is not the solution to solve the problem. A device is useless without the capability to use it. Policy must evolve from providing digital access to building digital capability.

The first target should require moving beyond mere hardware distribution**.** State and central governments must pair device distribution with connectivity subsidies.

Providing a student with a smartphone does not pay for the high-speed data required for online research. Policies should mandate subsidised or free broadband access for students from low-income families. Digital literacy training should also become a mandatory, credit-bearing part of the first-year university curriculum. This training must go beyond basic typing and focus on academic digital skills. This can include skills like navigating academic databases and utilising analytical software.

Secondly, targeted interventions are required for the marginalised groups. Treating all the students as homogeneous and applying the umbrella digital policy will not ensure equality; rather, it will only expand existing gaps. The results from the study show that students from weaker groups like SC/ST, and students belonging to the Muslim community and from rural areas face a triple disadvantage. Undertaking universal policies often fail to reach these specific groups. Therefore, adoption of policies which are targeted and intersectional in nature is the need of the hour. There is a need for building dedicated digital resource centres in rural, minority-dominated areas or educationally backward blocks. These centres must provide reliable electricity, high-speed internet, and hardware access beyond the standard college hours.

Thirdly, it is important for the institutions to take responsibility. To solve the problem of digital capability, one cannot totally rely on the families of the students. The universities/colleges may take up an active role in ensuring a level playing field. The higher education institutions must invest heavily in developing the digital infrastructure. This would involve expanding the Wi-Fi networks, which will be available 24x7 for students. Further, provision and availability of computer laboratories should be made in the evening. Only by providing a strong digital environment on campus can institutions directly counter the digital deprivation students face at home. Finally, professors/lab-technicians must be trained to recognise digital inequality. They must be trained to handle digital inequality, and pedagogical strategies should not assume that all students have equal internet access at home.

6. Conclusion

This paper aimed to reinterpret the assessment of digital inequality in higher education. Using Sen's (1999) Capability Approach framework on a group of students in West Bengal moves the conversation beyond just owning a device. The proof is clear that digital skills are a huge factor in how well students do in school. It mediates almost 42.8 per cent of the academic benefit that has long been associated with family wealth. More importantly, the results from the study point to the existence of a serious Digital Paradox. Economic progress does not necessarily dismantle historical social barriers as it is seen. The students from the general category had their digital skills improved a lot when their family's income went up, but the impact on students from lower castes was a lot less. This shows that caste and social status still dictate who benefits from new technologies. Also, the combination of rural geography, minority religion, and lower caste status makes it almost difficult for students to get online education and access resources.

As India moves forward with the National Education Policy 2020's vision of digital-first, we need to face these undesirable yet undeniable facts. Technology isn't just a natural way to make things fair. If we don't regulate digital tools, they will become engines of social reproduction. This will quietly enforce the old inequalities in a new way, creating a digital divide. To create a truly fair higher education system, policy needs to focus on what the student can do, not just the wires that connect the classroom. If the National Education Policy 2020's digital-first rule isn't followed, it could make old inequalities worse. For true digital integration to happen, policy frameworks need to go beyond just giving out hardware and actively build digital skills that cross different areas.

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