"Impact of Poverty and Lack of Technology Usage on the Digital Divide Among Gen Z"

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Abstract

The digital divide among young people is often explained by poverty and by low use of technology, and this study examines how far both explain it among Gen Z college students. Primary data were collected with an online questionnaire using 5-point Likert statements. The form returned 101 rows, but 69 were exact duplicates (same timestamp and answers), so N = 32 unique responses were analysed. Descriptive statistics, Cronbach's alpha, chi-square tests, one-way ANOVA, Pearson correlation and linear regression were used. A digital divide score was built from five statements on missed classes, electricity, network, shared devices and perceived inequality (M = 2.59 on a 5-point scale; 43.8% Low, 43.8% Moderate and 12.5% High). The chi-square tests found that digital divide level was associated with gender ($\chi^2(2) = 6.03$, $p = .049$; permutation $p = .033$), with 76.5% of male students at Moderate or High level against 33.3% of female students, but not with age, year of study or institution type. The ANOVA showed no significant difference in the digital divide score across family income groups ($F(3, 28) = 1.01$, $p = .405$), and income did not predict the score ($R^2 < .001$, $p = .981$). Technology usage did not significantly predict the score either ($\beta = .29$, $p = .111$). In the multiple regression, the four predictors explained 49.2% of the variance (adjusted $R^2 = .417$, $p < .001$), but only affordability was significant ($\beta = .64$, $p < .001$). Poverty and technology usage were not significant once affordability was included. The sample is very small, non-random and self-reported, so these results are preliminary.

Keywords: digital divide, Gen Z, poverty, technology usage, affordability, chi-square, ANOVA, linear regression.

Introduction

Technology now plays a central role in the way students attend classes, submit work and find study material, so unequal access to it can translate into unequal access to education. Online classes, learning management systems, college portals and digital reference material all assume a student has a working device, an affordable data connection, steady electricity and the skills to use them. Each of these assumptions may be violated for students from poor households.

The digital divide is the gap between those who can use digital technology effectively and those who cannot. It is usually described at several levels: unequal access to devices and connectivity, unequal skills and use, and unequal benefits from use. In India, the divide follows income, caste, education, gender and region, and it became more visible when learning moved online.

Gen Z, the generation born roughly between 1997 and 2012, has grown up with smartphones and the internet and is often described as "digital native". Being digitally native, however, does not mean being digitally equal. A Gen Z student from a poor family may own a phone but share it, rely on prepaid data, and live where power and network are unreliable. The present study therefore asks whether poverty and low technology usage are associated with the digital divide among Gen Z college students.

Research Gap

Most earlier studies look at the digital divide only at the state or national level, relying on broad statistics such as network coverage and device availability. Because of this, the daily technology problems faced by Gen Z remain largely unexplored, and very little research looks at how poverty and low technology usage work together to keep young people from adopting technology. Looking only at network towers or general data cannot explain why Gen Z still struggles to afford and use digital tools, even when the internet is available nearby. This study fills that gap by focusing directly on Gen Z and gives a clear and practical understanding of how poverty and low technology usage together create the digital divide among them.

Conceptual Framework

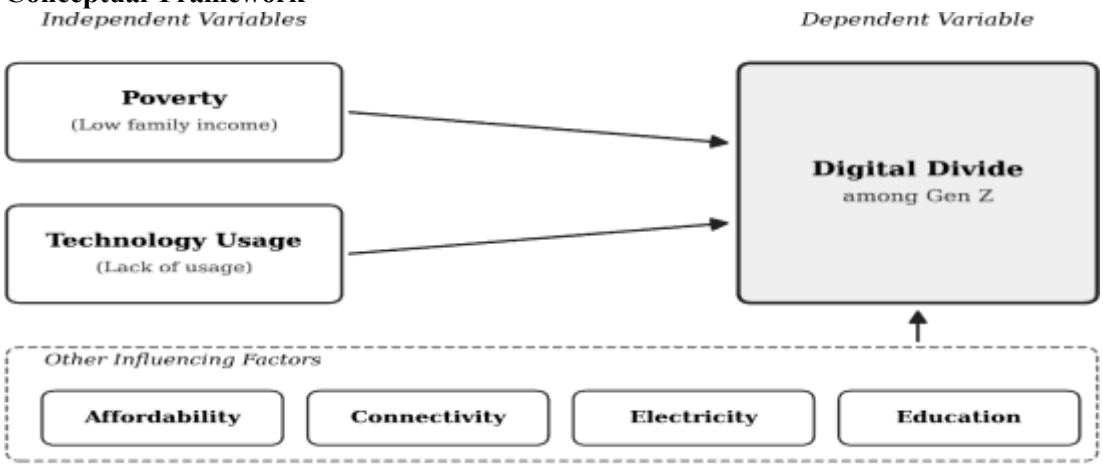


Figure 1: Conceptual Framework of the Study

[Figure 1: Conceptual Framework of the Study. Insert the figure from your draft here.]

Table A. Variables in the framework

Block	Variable	Measured by
Independent	Poverty (POV)	Family income band, reversed so that a higher score means poorer
Independent	Technology usage (TU)	Q22, Q24, Q26, Q28 (skill, study use, scholarship search, benefit)
Other influencing factors	Affordability (AFF)	Q15, Q16 (income limit on devices, data cost burden)
Other influencing factors	Connectivity (CON)	Home internet and network signal rating
Other influencing factors	Electricity, education	Q18; year of study

Dependent	Digital divide (DD)	Q17–Q21 (missed classes, electricity, network, shared device, perceived inequality)

Review of Literature

Stefani (2025) examines digital poverty in the Western Balkans, assessing how ICT and digital financial services drive economic inclusion. Grounding the inquiry in resource-appropriation and capability theories, the study connects digital skills, education and national policy frameworks.
Key findings show that expanding physical infrastructure fails to bridge regional divides without concurrently resolving skills deficits and affordability issues. The paper delivers a valuable
multi-sectoral synthesis for an understudied region, while underscoring the necessity for future empirical and longitudinal validation.

Tayo et al. (2016) explore the lived experiences and perceptions of computer usage and internet accessibility among low-income community members in southwest Nigeria. The study examines how prohibitive costs, infrastructural deficits and lack of digital skills perpetuate the digital divide, limiting economic and career opportunities. Key findings reveal severe access barriers, with 70% lacking personal computers and only 20% able to afford sustained internet access despite high motivation for ICT-driven advancement. By capturing qualitative, face-to-face insights from underrepresented rural populations, the research provides grounded localized evidence on socio-economic exclusion, though constrained by a localized sample size.

Venkat (2001) examines whether market-driven digital divide initiatives reduce poverty, using the U.S. as a benchmark for developing economies. The conceptual inquiry evaluates the interplay between rapid technological expansion, rising income inequality and unresolved fundamental socio-economic needs. Findings demonstrate that technological proliferation left poverty rates static (about 12%), showing digital disparity is a symptom rather than the cause of economic inequality. The paper delivers a vital contrarian critique of techno-optimism, arguing that core material deprivation must be addressed before technology can drive inclusion.

Mulyaningsih et al. (2020) examine digital diffusion and literacy patterns across urban poor neighborhoods in Magelang City, Indonesia. The empirical study analyzes device ownership and usage variations across demographic dimensions, including age, gender, occupation and localized poverty levels. Findings reveal stark intra-community divides, with over 65% lacking smartphones and older cohorts (40+) facing severe exclusion (over 90% non-ownership). The paper provides valuable micro-level disaggregated data on marginalized urban pockets, though constrained by a small, single-city sample size.

Akanbi and Akanbi (2012) evaluate the impact of ICT access disparities on national poverty trends across Nigeria. The study tracks multi-decade poverty metrics against state-level penetration rates of traditional and modern communication technologies. Findings demonstrate marginal poverty alleviation gains, with extreme deficits in personal computing (0.9%) and internet access (0.5%) limiting developmental outcomes. The paper establishes a critical macro-level baseline on regional digital gaps, though constrained by descriptive secondary datasets.

Aker and Mbiti (2010) investigate how mobile phone diffusion impacts agricultural market performance and consumer welfare across Sub-Saharan Africa. The empirical study evaluates structural transmission channels, including price transparency, search cost reduction and mobile financial services. Findings demonstrate that mobile adoption significantly reduces spatial price dispersion in food markets, improving overall producer efficiency. The paper establishes a foundational baseline on mobile ICT adoption, while emphasizing that connectivity cannot substitute for deficient transport and physical infrastructure.

Chinn and Fairlie (2007) examine global determinants of cross-country disparities in computer and internet penetration across 161 nations. The econometric analysis employs decomposition techniques to evaluate the

explanatory roles of income, telecom infrastructure, human capital and regulatory quality. Findings reveal that per capita income differentials and telecommunications infrastructure constitute the primary drivers of the worldwide digital divide. The study delivers a definitive macro-level econometric benchmark on global ICT inequalities, though constrained by aggregate national cross-sectional data.

Ragnedda and Muschert (2013) conceptualize the third-level digital divide, shifting focus from access and literacy to offline outcome inequalities. Grounded in Weberian stratification theory, the treatise analyzes how existing social capital determines the tangible benefits derived f rom internet usage. The authors argue that socio-economically marginalized cohorts systematically extract lower offline returns from digital engagement, compounding pre-existing structural disparities. The work provides a seminal theoretical framework repositioning digital inequality research around real-world socio-economic stratification and capital conversion.

Tang et al. (2024) examine the empirical relationship between rural e-commerce expansion and household multidimensional poverty alleviation. The micro-econometric inquiry models transmission pathways across agricultural market efficiency, income diversification and household vulnerability reduction. Findings indicate that e-commerce adoption significantly lowers multidimensional poverty, with welfare gains concentrated among digitally literate households. The paper delivers robust micro-level evidence on digital market integration, while highlighting persistent capability gaps across marginalized agrarian groups.

Flaminiano et al. (2021) evaluate the role of digital literacy and platform adoption in fostering micro-enterprise resilience during economic disruptions. The empirical study examines operational adaptations across mobile commerce, digital payment integration and social media marketing in developing markets. Findings reveal that digital competencies significantly enhance revenue stability and business survival, serving as a buffer against market shocks. The research provides valuable micro-level insights connecting digital capability to enterprise viability, while noting persistent infrastructural and skill deficits.

Mittal and Mehar (2012) investigate how mobile telephony and mobile-enabled information services impact smallholder agricultural productivity across rural India. The empirical study analyzes how mobile information delivery reduces market search costs, bridges agricultural input bottlenecks and overcomes rural information asymmetry. Findings demonstrate that mobile-based extension services yield measurable gains (12–20% in crop yields), though structural digital divides persist in tribal and illiterate farming segments. The paper delivers vital micro-level evidence on ICT-driven agrarian efficiency, while emphasizing that connectivity requires trustworthy, timely information and complementary physical infrastructure.

Jafar, Ananthpur and Venkatachalam (2023) examine the structural digital divide and online educational accessibility across marginalized communities in Tamil Nadu, India. The empirical inquiry assesses how unequal ICT infrastructure, device constraints and digital competency gaps affect distance-learning engagement during extended school closures. Findings reveal that pre-existing socio-economic divides severely amplify educational inequalities, imposing heavy financial burdens on low-income households and increasing dropout risks. The study provides critical state-level evidence demonstrating that rapid educational digitization reproduces social stratification without targeted public institutional support.

Objectives

1. To study the level of digital divide among Gen Z.
2. To examine the impact of poverty and low family income on the digital divide among Gen Z.
3. To examine the impact of lack of technology usage on the digital divide among Gen Z.
4. To identify other factors (education, affordability, electricity, internet connection) that affect technology use among Gen Z.
5. To suggest ways to reduce the digital divide among Gen Z.

Hypotheses

H1: There is a significant association between digital divide level and gender, place of residence and course among Gen Z (chi-square).

H2: There is a significant difference in the mean digital divide score across different family income groups of Gen Z (one-way ANOVA).

H3: There is a significant negative relationship between family income and the digital divide among Gen Z (simple linear regression).

H4: There is a significant negative relationship between technology usage and the digital divide among Gen Z (simple linear regression).

H5: The joint effect of poverty, technology usage, affordability and internet connectivity on the digital divide among Gen Z is significant (multiple linear regression).

Note: the survey data do not contain place of residence or course, so for H1 the digital divide level was tested against gender, age, year of study and institution type instead.

Research design

The study is a quantitative cross-sectional survey. Primary data were gathered directly from Gen Z college students through a structured, self-administered questionnaire made available online.

Data collection and sampling

The sampling technique was convenience sampling, in which respondents were chosen based on their availability and willingness to participate. The online form was filled in on 1 and 2 September 2026. [Author to fill in: number of questionnaires circulated and the colleges covered.] The data file had 101 rows, but 69 rows were duplicates of earlier rows (same timestamp and identical answers) and were deleted, leaving N = 32 unique responses.
Respondent names were not used. The findings cannot be generalised to all Gen Z students as the sample is non-random and small.

Instrument

The questionnaire has two sections. Part A gathers background and access details: age, gender, year of study, type of institution, monthly family income, BPL card, family size, smartphone, laptop, home internet, internet use for study, electricity, network signal and main uses of the internet (Q1–Q14). Part B has 14 statements (Q15–Q28) rated on a 5-point Likert scale (1 = strongly disagree to 5 = strongly agree). They were grouped into four constructs:

- Digital divide (DD): Q17–Q21 (5 items), missed classes for lack of data or device, poor electricity, weak network, shared device and perception that richer students have better access. Higher means a larger divide.

- Technology usage (TU): Q22, Q24, Q26, Q28 (4 items), skill to use devices, use of the internet for study material, use for scholarships and benefit from technology. Higher means more usage.

- Affordability (AFF): Q15 and Q16 (2 items), family income limits buying a device and data cost is a burden. Higher means affordability is a bigger problem.

- Connectivity (CON): the average of the home internet answer (yes = 5, no = 1) and the network signal rating (1 = very poor to 5 = very good). Higher means better connectivity.

Poverty (POV) is the monthly family income band reversed (1 = above ₹5,00,000 to 4 = ₹5,000–

₹10,000) so that a higher score means poorer; the income band itself (1–4) was used in H2 and H3. A construct score

is the average of its items (range 1–5). A score of less than 2.50 is considered Low, 2.50–3.49 Moderate and 3.50 or higher High. The remaining Q23, Q25 and Q27 were not used in these constructs. For Q18, Q20 and Q21 one respondent each left the item blank, and the score was taken from the items answered.

Statistical tools

Data preparation was done in Microsoft Excel (coded data with index formulas) and the results were checked in Python (SciPy). Cronbach's alpha was used to test reliability. Chi-square tests of independence, one-way ANOVA with Tukey post-hoc comparisons, Pearson correlation and ordinary least squares regression were used at the 5% significance level. For the chi-square tests the digital divide level was collapsed to Low versus Moderate/High because only 4 students scored High. Because many expected counts were below 5, a Fisher exact test (2 × 2 tables) or a permutation p-value (larger tables) is given as a check.

Respondent profile

Table 1. Profile of respondents (N = 32)

Variable	Category	Count	Percent
Age	18–20 years	23	71.9%
	21–23 years	7	21.9%
	Above 23 years	2	6.3%
Gender	Male	17	53.1%
	Female	12	37.5%
	Other	3	9.4%
Year of study	1st year	6	18.8%
	2nd year	4	12.5%
	3rd year	19	59.4%
	Final year	3	9.4%
Institution	Private	30	93.8%
	Government	2	6.3%
Monthly family income	₹5,000–₹10,000	6	18.8%

Variable	Category	Count	Percent
	₹10,001–₹1,00,000	5	15.6%
	₹1,00,000–₹5,00,000	11	34.4%
	Above ₹5,00,000	10	31.3%
BPL card	Yes	4	12.5%
	No	19	59.4%
	Not sure	9	28.1%
Access	Smartphone	30	93.8%
	Personal laptop	24	75.0%
	Home internet	22	68.8%
	Regular electricity	23	71.9%

Source: Survey data. Percentages may not sum to 100 due to rounding.

Most respondents were aged 18–20 (71.9%), male (53.1%), in their third year (59.4%) and at private institutions (93.8%). Smartphones were almost universal, but 25.0% had no personal laptop and 31.3% had no home internet. The groups "Above 23" (n = 2), "Other" gender (n = 3), government institutions (n = 2) and BPL card holders (n = 4) are very small, so group comparisons have limited power.

Reliability

Table 2. Descriptive statistics and reliability of the constructs

Construct	Items	Mean	SD	Cronbach's α	Reliability
Digital divide (DD)	5	2.59	1.06	.828	Good
Construct	Items	Mean	SD	Cronbach's α	Reliability
Technology usage (TU)	4	3.76	1.20	.895	Good
Affordability (AFF)	2	2.39	0.98	.226	Poor

Connectivity (CON)	2	3.55	1.10	—	Two unrelated indicators (r = .03)

Scale 1–5. The digital divide and technology usage scales exceed the .70 criterion. The two affordability items are only weakly related (r = .13), and the home internet and network signal items are unrelated (r = .03), so AFF and CON are rough composites and their results should be read with care.

Level of digital divide and its factors

Table 3. Respondents classified by construct level

Construct	Low	Moderate	High	% High
Digital divide (DD)	14	14	4	12.5%
Technology usage (TU)	6	5	21	65.6%
Affordability problem (AFF)	15	12	5	15.6%
Connectivity (CON)	5	8	19	59.4%

Low < 2.50; Moderate 2.50–3.49; High ≥ 3.50.

The level of digital divide in this sample is low to moderate: 43.8% of students scored Low, 43.8% Moderate and 12.5% High (M = 2.59). Technology usage was high for most (65.6%). The items with the highest levels of agreement were knowing how to use a smartphone or computer (Q22, 3.97) and using the internet for study material (Q24, 3.75). Among the divide items, poor electricity affecting online study (Q18, 3.03) was highest and having missed classes for lack of data or a device (Q17, 1.97) was lowest. So the typical student reports little disruption, but about one in eight faces a high divide.

Correlation

Table 4. Pearson correlation matrix (N = 32)

	DD	POV	TU	AFF	CON
Digital divide (DD)	1	−.004	.287	.691*	−.158
Poverty (POV)	−.004	1	−.228	.008	−.705*

Technology usage (TU)	.287	−.228	1	.275	.242
Affordability (AFF)	.691*	.008	.275	1	−.198
Connectivity (CON)	−.158	−.705*	.242	−.198	1

Note: an asterisk marks a correlation significant at $p < .001$ (two-tailed). All other correlations are not significant.

The digital divide score is strongly and positively correlated with affordability problems ($r =$ .691). It is not significantly correlated with poverty ($r = -.004$), technology usage ($r = .287$, $p =$ .111) or connectivity ($r = -.158$, $p = .389$). Poverty and connectivity are strongly and negatively correlated ($r = -.705$), so poorer students had weaker connectivity, which agrees with the access findings; the high correlation is examined for multicollinearity in Section 7.7. The positive correlation between technology usage and the divide score is the opposite of the expected direction, though it is not significant.

Chi-square tests of independence

Table 5. Chi-square test results (digital divide level: Low vs Moderate/High; N = 32)

Association tested	χ^2	df	p	Cramér's V	Exact / permutation p
Gender × DD level	6.026	2	.049	.434	.033 (permutation)
Age group × DD level	0.741	2	.690	.152	.841 (permutation)
Year of study × DD level	1.845	3	.605	.240	.669 (permutation)
Institution type × DD level	1.659	1	.198	.228	.492 (Fisher)
Family income (low/high) × DD level	0.020	1	.888	.025	1.000 (Fisher)

BPL status × DD level	0.942	2	.625	.172	.672 (permutation)

DD level was collapsed to Low versus Moderate/High (14 and 18 students) because only 4 students scored High. Place of residence and course were not in the data file, so age, year of study and institution type were used instead. Many expected counts were below 5 (the gender test has a minimum of 1.31), so the exact or permutation p-values are the more reliable check.

Only gender was significantly associated with digital divide level, and the result is supported by the permutation test ($p = .033$). 76.5% of male students (13 of 17) were at Moderate or High level, against 33.3% of female students (4 of 12) and 1 of 3 students of "Other" gender. Collapsing gender into male versus female/other gives $\chi^2(1) = 6.03$, $p = .014$ (Fisher $p = .031$). Digital divide level was not significantly associated with age group, year of study, institution type, family income or BPL status. H1 is therefore partly supported (gender only, and place of residence and course could not be tested).

One-way ANOVA

Table 6. One-way ANOVA of the digital divide score by group

Grouping factor	F	df	p	η^2	Result
Family income (4 bands)	1.007	3, 28	.405	.097	Not sig.
Family income (low/high)	0.136	1, 30	.715	.005	Not sig.
BPL status (3)	1.330	2, 29	.280	.084	Not sig.
Gender (3)	4.144	2, 29	.026	.222	Significant
Age (3)	0.741	2, 29	.486	.049	Not sig.
Year of study (4)	1.929	3, 28	.148	.171	Not sig.
Internet use for study (3)	0.474	2, 29	.627	.032	Not sig.
Electricity (2)	0.000	1, 30	.984	.000	Not sig.

Grouping factor	F	df	p	η^2	Result
Network signal (3)	0.190	2, 29	.828	.013	Not sig.
Laptop (2)	0.496	1, 30	.487	.016	Not sig.
Home internet (2)	0.141	1, 30	.710	.005	Not sig.

Levene's test was not significant for any comparison (all $p > .20$), so equal variances can be assumed.

Table 7. Group means (SD) of the digital divide score

Factor	Group	n	DD mean (SD)	Tukey HSD
Family income	₹5,000–₹10,000	6	2.20 (0.57)	—
	₹10,001–₹1,00,000	5	3.28 (0.77)	vs ₹5,000–₹10,000: p = .354
	₹1,00,000–₹5,00,000	11	2.60 (1.20)	no pair significant
	Above ₹5,00,000	10	2.48 (1.21)	no pair significant
Gender	Female	12	1.98 (0.70)	—
	Male	17	3.04 (1.16)	vs Female: p = .020
	Other	3	2.53 (0.42)	vs Female: p = .658; vs Male: p = .690

The digital divide score did not differ significantly across family income groups, so H2 is not supported. The pattern was not in a straight line: the highest score was in the ₹10,001–₹1,00,000 band (3.28, n = 5) and the lowest in the ₹5,000–₹10,000 band (2.20, n = 6), but no pair of income groups differed significantly in the Tukey test. The only significant difference was by gender: male students scored higher on the divide (3.04) than female students (1.98; Tukey p = .020; Kruskal–Wallis p = .024). Year of study showed an upward trend from 1st year (1.77) to final year (3.00) that was not significant (p = .148).

Linear regression

Model 1: H3, simple regression. The digital divide score was regressed on family income band (1 = ₹5,000–₹10,000 to 4 = above ₹5,00,000).

Table 8. Simple linear regression (dependent variable: DD)

Model	Predictor	B	SE	β	t	p
1	Constant	2.582	0.527	—	4.898	< .001
	Family income band	0.004	0.177	.004	0.024	.981
2	Constant	1.636	0.611	—	2.678	.012
	Technology usage (TU)	0.255	0.155	.287	1.642	.111

Model 1: R^2 = .000, adjusted R^2 = −.033, F(1, 30) = 0.001, p = .981; 95% CI for B: −0.357 to 0.365. Model 2: R^2 = .082, adjusted R^2 = .052, F(1, 30) = 2.695, p = .111, SE of estimate = 1.036; 95% CI for B: −0.062 to 0.572.

Family income does not predict the digital divide score at all (β = .004), so H3 is not supported. Technology usage explains 8.2% of the variance, and its sign is positive (higher usage, higher divide score), which is the opposite of the negative relationship in H4; it is also not significant. H4 is not supported.

Model 3: H5, multiple regression. Poverty, technology usage, affordability and connectivity were entered together.

Table 9. Multiple linear regression (dependent variable: DD)

Predictor	B	SE	β	t	p	VIF
Constant	0.960	1.219	—	0.788	.438	—
Poverty (POV)	−0.047	0.191	−.049	−0.247	.807	2.07
Technology usage (TU)	0.110	0.133	.124	0.823	.418	1.20
Affordability (AFF)	0.692	0.164	.639	4.233	< .001	1.21

Connectivity (CON)	−0.093	0.200	−.096	−0.465	.646	2.25

R^2 = .492, adjusted R^2 = .417, F(4, 27) = 6.549, p < .001, SE of estimate = 0.812. Durbin–Watson = 1.86.

The model is significant and explains 49.2% of the variance in the digital divide score, so H5 is supported as a joint effect. However, only affordability is a significant predictor (β = .639): each one-point increase in the affordability problem is associated with a 0.69-point higher divide score. Poverty, technology usage and connectivity add nothing once affordability is included.

The VIF values are all below 2.3, so multicollinearity is not a problem even though poverty and connectivity are correlated (r = −.705). Residuals are normally distributed (Shapiro–Wilk p = .208) and show no autocorrelation. Note that the affordability item on data cost (Q16) is also related to the divide item on missed classes (Q17), so part of this strong effect may be due to similar wording, and AFF had low reliability (α = .23).

Robustness and data-quality check

Duplicates. The original file had 101 rows, but 69 had the same timestamp and answers as earlier rows; the same 32 responses repeat about three times. Analysing the copies as separate students would have inflated the sample three-fold and made small differences look significant, so only the 32 unique responses were used. [Author to confirm that no other genuine responses exist.]

Straight-lining. One respondent (3.1%) gave the same score (5) to all 14 statements and reported never using the internet for study, which is inconsistent. When this respondent was removed (n = 31) the results did not change: the multiple regression stayed significant (R^2 = .395, adjusted R^2 = .302, p = .009) with only affordability significant (β = .578, p = .001), and the income regression stayed non-significant (p = .635).

Small groups. When the 4 students aged above 23 or of "Other" gender were removed (n = 28), the multiple regression was again significant (R^2 = .496, adjusted R^2 = .408, p = .003) with only affordability significant (β = .638, p = .001), and the ANOVA by income stayed non-significant (p = .499). The main finding, that affordability is the strongest correlate of the digital divide while family income is not, is therefore stable across these checks.

Summary of Findings

The digital divide among the Gen Z students surveyed is low to moderate (M = 2.59; 43.8% Low, 43.8% Moderate and 12.5% High), and technology usage is high for most (M = 3.76; 65.6% High).

H1 is partly supported. Digital divide level was significantly associated with gender (p = .049; permutation p = .033), with 76.5% of male students at Moderate or High level against 33.3% of female students. It was not associated with age, year of study, institution type, income or BPL status. Place of residence and course could not be tested as the data have no such variables.

H2 is not supported. The digital divide score did not differ significantly across the four family income groups (F(3, 28) = 1.01, p = .405). The only significant ANOVA difference was by gender (p = .026).

H3 and H4 are not supported. Family income did not predict the digital divide score (R^2 < .001, p = .981), and technology usage did not predict it either (β = .29, p = .111, and in the opposite direction to the hypothesis).

H5 is supported as a joint effect. The four predictors explained 49.2% of the variance in the digital divide score (adjusted R^2 = .417, p < .001), but only affordability was a significant predictor (β = .64, p < .001). This finding was stable after removing a straight-lining respondent and the students from very small groups.

Discussion

The main finding is that affordability, and not family income or technology usage, is the strongest correlate of the digital divide among these Gen Z students. Students who said that income limits their ability to buy devices and that data cost is a burden were also the ones who reported missed classes, poor electricity, weak networks, shared devices and a feeling that richer students have better access. This agrees with studies which conclude that expanding infrastructure does not close the divide unless affordability and skills are also addressed (Stefani, 2025; Aker & Mbiti, 2010) and that cost is a major barrier for low-income users (Tayo et al., 2016).

The finding that family income did not predict the divide, and that the income pattern was not in a straight line, is different from studies that find income to be the main driver of digital inequality (Chinn & Fairlie, 2007; Agrawal & Asrani, 2018). There are three possible explanations, none of which this survey can confirm. First, the sample is small (the lowest income band has 6 students), so a real effect may have been missed. Second, the sample is made up of students in college, who are already a more favoured group than Gen Z as a whole. Third, students with no home internet at all may report fewer problems with online study because they depend less on it. This also fits the view that digital disparity can be a symptom of wider material deprivation and not only its cause (Venkat, 2001).

Technology usage did not reduce the divide score, and the sign was positive. This may mean that students who use technology most are also the ones who notice its limits most. It does not mean that using technology causes a larger divide. The gender result (male students scoring higher on the divide than female students) is unexpected and would need a larger sample, since only 12 female and 3 "Other" students were in the sample. Studies on gendered barriers in India usually find women to be at a disadvantage (Priti & Vaish, 2025), so this result should be checked before any conclusion is drawn.

The weak results for poverty and connectivity should not be read as proof that there is no effect. With N = 32 the tests have little power, and the AFF and CON measures were rough. The benefit students get from use, which is the third level of the divide (Ragnedda & Muschert, 2013), was also not measured here.

Suggestions and Implications

Affordability should be the first target of efforts to reduce the digital divide among Gen Z. Subsidised data packs, low-cost or loaned laptops and phones, and device-sharing schemes in colleges would address the problems that most strongly accompanied a higher divide score.

Colleges and local governments could provide free campus Wi-Fi, study rooms with power backup and offline-friendly or recorded lessons, so that poor electricity and weak networks do not mean missed classes.

Programs should not assume that low family income alone identifies the students who need help. Colleges can ask students directly about the cost of data and devices and about missed classes, and target support on that basis.

Digital skills support should continue for all students, since even those who use technology a great deal reported barriers.

Further work is needed on gender differences, because the divide score was higher for male students in this sample, which differs from most reports.

Limitations and Future Research

The study has several limitations. The sample is very small (N = 32 after 69 duplicate rows were removed), non-random and almost entirely from private institutions (93.8%), so it cannot represent Gen Z in India. Some groups are tiny: 2 students aged above 23, 3 of "Other" gender, 2 in government institutions and 4 BPL card holders, so tests for those groups have little power, and several chi-square tables had expected counts below 5. Place of residence and course were not collected, so H1 could only be tested partly. The digital divide score is a short self-reported measure built from five statements ($\alpha = .83$), the affordability measure had low reliability ($\alpha =$ .23), and the connectivity measure combines two unrelated indicators. Affordability and the

divide score share similar content, which may inflate their relationship. All measures are perceptions taken at one point in time, so no cause and effect can be shown. One respondent answered every statement with the same score. Future studies should use a larger, random, multi-district sample, include place of residence and course, use objective measures of device and data use, and use structural equation modelling to test the paths from poverty and affordability to technology use and the divide.

Conclusion

This study examined the impact of poverty and lack of technology usage on the digital divide among Gen Z, using 32 unique college student responses. The digital divide was low to moderate for most students. Family income and technology usage did not significantly predict the divide score, and the divide score did not differ significantly across income groups. Affordability, meaning the cost of devices and data, was the only significant predictor in a model that explained about half of the variance in the divide. Gender was the only factor significantly associated with the divide level. Considering the small sample, the self-reported measures and the data-quality issues, the results are preliminary and should be validated in a larger and more representative sample.

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