"DIGITAL DIVIDE AND DIGITAL ECONOMY PARTICIPATION AMONG COLLEGE STUDENTS IN VISAKHAPATNAM"

Mrs. I. Ramya Deepthi

Research Scholar,
Department of Economics,
College of Arts and Commerce,
Andhra University, Visakhapatnam, Andhra Pradesh, India.

Prof. B. Lilly Grace Eunice

Professor,
Department of Economics,
College of Arts and Commerce,
Andhra University, Visakhapatnam, Andhra Pradesh, India.

ABSTRACT

Access to smartphones and the internet has become part of everyday student life, but being connected does not necessarily mean being able to participate fully in the digital economy. This paper investigates how different aspects of the digital divide relate to digital economy participation among 404 undergraduate students from different degree colleges in Visakhapatnam District, Andhra Pradesh through a questionnaire. The study examines six indices: first-level digital access, second-level digital skills and use, third-level digital outcomes, technology attitude, digital privacy and artificial intelligence. Multiple linear regression was used to assess their associations with the Digital Economy Participation Index. The model was statistically significant, $F(6, 397) = 10.168$, $p < .001$, and explained 13.3% of the variation in participation (adjusted $R^2 = .120$). Third-level digital outcomes ($\beta = .278$, $p < .001$) had the strongest positive association, followed by technology attitude ($\beta = .108$, $p = .033$) and second-level digital skills and use ($\beta = .104$, $p = .049$). Access, privacy and AI indices were not significant independent predictors at the 5% level. The findings suggest that digital inclusion initiatives in higher education should pay attention not only to connectivity but also to the practical capabilities and experiences that help students benefit from it. As the study is based on a cross-sectional survey, the results are interpreted as associations rather than causal effects.

Keywords: Digital Divide; Digital Economy Participation; Undergraduate Students; Digital Skills; Technology Attitudes; India; Multiple Regression

1. INTRODUCTION

For many undergraduate students, a phone and an internet connection are everyday necessities. Students use digital services to pay fees, purchase goods, access learning materials and explore employment opportunities. Yet students with similar levels of connectivity may use these opportunities very differently. Some are confident navigating online services, while others face difficulties even when the technology is physically available. This difference raises an important question: what matters most for meaningful participation in the digital economy?

Digital divide scholarship increasingly distinguishes between inequalities in material access, internet skills and usage, and beneficial outcomes (van Dijk, 2005; Hargittai, 2002; Scheerder et al., 2017). This perspective is relevant to higher education because students may be connected yet differ substantially in their ability and willingness to use digital opportunities. Digital economic participation therefore offers a useful outcome through which to examine the relevance of multiple digital inequality dimensions together.

Against this background, the present study draws on questionnaire responses from 404 undergraduate students attending different degree colleges in Visakhapatnam District, Andhra Pradesh. It brings together six dimensions of students' digital experience to examine which ones are associated with their participation in digital economic activities when considered simultaneously. The analysis is intended to inform college-level digital inclusion strategies without assuming that access by itself is enough.

2. REVIEW OF LITERATURE AND CONCEPTUAL FRAMEWORK

2.1 From connectivity to multidimensional digital inequality

An access-focused account of digital inequality distinguishes people with digital resources from those without them. van Dijk (2005), however, conceptualises access as a process that involves more than possession of infrastructure, including motivation, skills and use. Hargittai (2002) identifies the second-level digital divide as variation in individuals' online skills even among internet users. Consequently, the same nominal internet connection need not produce the same capacity to navigate or evaluate online resources.

As internet availability expands, differences in the types and purposes of internet use become increasingly important. van Deursen and van Dijk (2014) show that inequalities may be reflected in divergent usage patterns rather than internet time alone. Scheerder et al. (2017) further emphasise a

third-level divide concerned with tangible benefits and outcomes. These perspectives imply that digital participation should be evaluated in relation to both enabling resources and the advantages that users derive from using them.

2.2 Technology attitude, privacy and artificial intelligence

Students' attitudes toward technology may be relevant to whether available tools are used for productive purposes. Positive orientation toward digital systems may coincide with engagement, perceived usefulness and willingness to experiment with unfamiliar services. Privacy-related knowledge and practices may also shape online engagement, although their role is not necessarily uniform across populations and activities. Likewise, familiarity with artificial intelligence may not directly translate into transactions or other economically relevant online participation. In the present study, these latter constructs are evaluated empirically rather than assumed to have a specific effect.

2.3 Research gap and expectations

The literature supplies a rationale for distinguishing access, capabilities and outcomes, but the relative contribution of these domains to students' digital economic participation is an empirical question. This study asks: Which of six measured digital-divide and technology dimensions show independent statistical associations with DEPI when included in the same regression model? The omnibus null hypothesis is that all six population regression slopes equal zero; the alternative is that at least one differs from zero. At the predictor level, the null hypothesis is a zero coefficient for each corresponding index. Directional expectations are not treated as established causal claims.

3. Materials and Methods

3.1 Research design and study area

The study adopted a quantitative, cross-sectional survey design to examine digital economy participation among undergraduate students in Visakhapatnam District, Andhra Pradesh, India. The district provides a useful setting for studying digital inequality because students attend degree colleges with varied educational and social contexts. The study used primary data collected directly from students rather than relying on institutional enrolment records or secondary datasets.

3.2 Study population, respondents and data collection

The study population comprised students pursuing undergraduate degree programmes in Visakhapatnam District. A structured questionnaire was distributed to 450 students attending different degree colleges in the district. Following collection, the questionnaires were scrutinised for completeness. Of the 450 questionnaires distributed, 404 were found to be complete and suitable for analysis; these formed the final study sample. The usable-questionnaire proportion was 89.78% (404/450). The available survey information does not establish a probability-based selection procedure, so no random sampling claim is made.

Data collection involved obtaining students' responses to questions on access to digital devices and internet services, digital skills and use, outcomes of digital engagement, attitudes toward technology, privacy-related practices, artificial intelligence and participation in digital economic activities. Spss software is used as tool for analysis the data.

3.3 Research instrument and measurement

The questionnaire served as the main data-collection instrument. It covered students' experiences of digital access, their ability to use digital technologies, the benefits they obtain from digital engagement, and their involvement in digital economic activities. Items were organised into seven composite measures: one dependent index and six explanatory indices. The analysis used scores normalised to a common 0–1 scale, with higher scores interpreted according to the direction of each respective index. Before calculating the indices, negatively worded items should be reverse-coded where applicable so that item directions are consistent.

The Digital Economy Participation Index (DEPI) is the dependent variable and the explanatory measures are First Level Digital Access Index (FLDAI), reflecting device and internet access; Second Level Digital Divide Index (SLDI), covering digital skills, competence and usage; Third Level Digital Divide Index (TLDI), covering outcomes of digital use; Technology Attitude Index (TAI), reflecting students' orientation toward technology; Digital Privacy Index (DPI); and Artificial Intelligence Index (AII)..

3.4 Analytical strategy and model specification

The principal analysis in this paper is ordinary least-squares (OLS) multiple linear regression. DEPI was entered as the dependent variable, while FLDAI, SLDI, TLDI, TAI, DPI and AII were entered simultaneously as independent variables using the Enter method in SPSS. This

specification estimates the association of each index with DEPI while holding the other five indices statistically constant.

$$\mathbf{DEPI_i = \beta_0 + \beta_1 FLDAI_i + \beta_2 SLDI_i + \beta_3 TLDI_i + \beta_4 TAI_i + \beta_5 DPI_i + \beta_6 AII_i + \varepsilon_i}$$

Here, β_0 denotes the intercept, β_1–β_6 the unstandardised regression coefficients, and ε_i the error term for student i. The overall null hypothesis was that all six slope coefficients equal zero. The alternative was that at least one coefficient differs from zero. A two-sided significance level of 0.05 was used for individual tests. Model performance was summarised using R, R^2, adjusted R^2, the standard error of the estimate and the F test. Individual coefficients were examined using B, standard errors, standardised beta values, t statistics, p values and 95% confidence intervals.

4. RESULTS

4.1 Regression model fit

Metric	Reported value
Valid observations	404
Multiple R	0.365
R^2	0.133
Adjusted R^2	0.120
Standard error of estimate	0.129
Durbin–Watson	1.968

Source: ccomputed from spss

The multiple regression model explained 13.3% of the observed variation in the Digital Economy Participation Index, with adjusted R^2 = .120. This is evidence of explanatory association but also indicates that most variation in the outcome remains unexplained by the six included predictors. The reported Durbin–Watson statistic was 1.968; while close to 2, its interpretation should be considered alongside the survey design and the absence of repeated or temporally ordered observations.

4.2 Overall model significance

Source	SS	df	MS	F	p
Regression	1.013	6	0.169	10.168	< .001
Residual	6.594	397	0.017		
Total	7.607	403			

Source : computed from spss

The omnibus model test was significant, $F(6, 397) = 10.168$, $p < .001$. The joint null hypothesis that the six predictor coefficients all equal zero is therefore rejected. This does not establish that each predictor has a unique association, nor does it establish that changing any predictor would cause a change in DEPI.

4.3 Individual predictor coefficients

Predictor	B	SE	β	t	p	95% CI for B	VIF
Constant	0.531	0.051	—	10.452	< .001	[0.431, 0.631]	—
FLDAI	0.074	0.038	0.100	1.951	.052	[−0.001, 0.148]	1.192
SLDI	0.110	0.055	0.104	1.979	.049	[0.001, 0.219]	1.269
TLDI	0.168	0.030	0.278	5.558	< .001	[0.108, 0.227]	1.150
TAI	0.171	0.080	0.108	2.136	.033	[0.014, 0.328]	1.172
DPI	−0.061	0.049	−0.065	−1.240	.216	[−0.157, 0.036]	1.244
AII	−0.026	0.041	−0.033	−0.630	.529	[−0.106, 0.055]	1.221

Source: computed from Spss

Note: B = unstandardised coefficient; SE = standard error; β = standardized coefficient; CI = confidence interval. Rounding may account for minor differences in reconstructed calculations.

The largest standardized association was observed for TLDI (β = .278, p < .001): higher reported beneficial digital outcomes were associated with higher DEPI, conditional on the other five indices. Technology attitude (β = .108, p = .033) and second-level digital skills/use (β = .104, p = .049) also had positive adjusted associations, although their standardized coefficients were small. The SLDI estimate is close to the 5% cutoff and merits cautious interpretation, especially in view of the six individual tests.

FLDAI was positive but did not reach the predefined 5% threshold (β = .100, p = .052; confidence interval included zero). It would be incorrect to interpret this as proof that access has no role in digital economic participation; the result indicates insufficient evidence for a unique association at this particular threshold and in this specific multivariable specification. DPI (β = −.065, p = .216) and AII (β = −.033, p = .529) also showed no statistically significant unique associations. Their negative point estimates do not justify concluding that privacy or AI awareness reduces participation.

Using the reported unstandardised coefficients, the fitted equation is:

Predicted DEPI = 0.531 + 0.074(FLDAI) + 0.110(SLDI) + 0.168(TLDI) + 0.171(TAI) − 0.061(DPI) − 0.026(AII).

5. Discussion

One important result is that the full regression model is statistically significant even though first-level access narrowly misses the 5 percent threshold in the adjusted analysis. This distinction matters. It does not mean that devices or connectivity are unimportant. Rather, among the students surveyed, differences in access did not explain a statistically detectable additional share of digital economy participation after skills, outcomes, attitudes and the other indices had been considered. A connection may open the door, but it does not tell us how confidently or productively a student will use what is available.

Third-level digital outcomes stood out as the strongest correlate of digital economy participation. Students who reported obtaining greater benefits from digital activities also tended to report greater involvement in the digital economy. This is consistent with the idea that what students gain from technology matters alongside whether they can access it. Still, the two indices measure related areas of experience; their questionnaire items should be reviewed carefully to ensure that the result is not partly driven by overlap between the measures.

Skills and attitudes also mattered, although their coefficients were smaller. A student who can search, evaluate and use online information effectively is better placed to navigate digital services. Similarly, a positive attitude toward technology may make digital transactions and unfamiliar platforms less intimidating. These findings fit with earlier scholarship that treats digital inequality as a question of skills, patterns of use and real-world benefits, not only infrastructure (Hargittai, 2002; van Deursen & van Dijk, 2014).

Neither the privacy nor the AI index had a statistically significant unique association with participation in this model. This should be interpreted cautiously. Privacy awareness and AI-related knowledge may still matter for safe and informed participation.

6. Practical and Policy Implications

The findings point toward a practical implication for degree colleges: expanding Wi-Fi coverage or making devices available is only part of an inclusion strategy. Students may also benefit from hands-on opportunities to practise digital transactions, use online public services, evaluate information, complete forms and make informed decisions about online platforms. Colleges can integrate such activities into digital literacy programmes, especially for students who have connectivity but limited experience using it for practical purposes.

A supportive environment matters as well. Peer mentoring, guided demonstrations and low-stakes practice can help students build confidence with unfamiliar digital services. Privacy and AI literacy remain worthwhile educational topics, but the findings of this survey should not be used to claim that they independently increase economic participation. The usefulness of proposed initiatives should be evaluated rather than assumed.

7. Conclusion

This study finds that digital economy participation is associated more clearly with beneficial digital outcomes, digital skills and favourable technology attitudes than with the access index alone. The six predictors jointly explain 13.3percent of observed variation in DEPI. The findings suggest that efforts to support participation should go beyond connectivity to help students develop digital capabilities and derive practical benefits from technology.

References

Hargittai, E. (2002). Second-level digital divide: Differences in people's online skills. First Monday, 7(4). https://doi.org/10.5210/fm.v7i4.942

Scheerder, A., van Deursen, A., & van Dijk, J. (2017). Determinants of Internet skills, uses and outcomes: A systematic review of the second- and third-level digital divide. Telematics and Informatics, 34(8), 1607–1624. https://doi.org/10.1016/j.tele.2017.07.007

van Deursen, A. J. A. M., & van Dijk, J. A. G. M. (2014). The digital divide shifts to differences in usage. New Media & Society, 16(3), 507–526. https://doi.org/10.1177/1461444813487959

van Dijk, J. A. G. M. (2005). The deepening divide: Inequality in the information society. SAGE Publications.