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Digital Dividends: Exploring The Impact Of Telecommunication Infrastructure On Economic Growth In India

Author: Suhaan Khurana

Abstract:
This paper examines the effect telecommunications infrastructure has on the growth of the Indian economy, emphasising the role that telecommunication usage and tools play on the GDP per capita and other economic parameters. It accesses information from different organisations, including the Telecom Regulatory Authority of India and UDISE+, to study the links between wireless and wireline users, user density, and school digital access and their impact on economic indicators. With advanced econometrics models, i.e. OLS regression, correlation analysis, random forests, step-wise regression, granger analysis, adfuller, and others, predictable solid relationships and directional relationships are proved to exist between the telecommunications background and GDP growth variable. The study results indicate that in India, there is a strong correlation between internet access in schools and wireless internet users. Moreover, it proposes policies to catalyse economic growth and digital adoption in India. It is a resource that policymakers can leverage to make the right decisions in harnessing the power of ICT for economic development.

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I. Introduction:

In the new digital world, a nation's digital landscape facilitates and enables communication and enhances business operations. Higher productivity and supply-chain activity lead to increased economic development and greater interconnectedness. This study investigates the economic impact of digital and telecommunications infrastructure across various states in India, focusing on how these technologies influence Gross Domestic Product (GDP) per capita and other financial metrics.

India presents a unique case study due to the vast digital landscape across states and the digital 2030 vision. The presence of digital infrastructure within schools – internet access and access to computers – provides an exciting outlook for understanding the effect on the number of wireless users(Wireless users in India have a mobile connection, including inactive users). Moreover, the research also examines the correlation between wireless use, wireline use, user density, and educational digital access. To analyse their implication on data including GDP, digital transaction volumes, digital transaction values, and the National Financial Switch (NFS) Automated teller machine (ATM) network (proxy of state-wise economic activity).

This study identifies the direct and indirect effects of digital infrastructure on economic growth, providing insights that could guide policymakers in prioritising investments and strategies for digital development.

II. Literature Review:

The links between technological advancements and economic growth can be observed as far back as the Solow-Swan theory, here, economic growth is seen as independent from economic activities within a model[1]. This theory transitioned to more progressive works by Romer (1990) and Lucas (1988)· which reference technologies as more endogenous[2]. Thus, it establishes technological advancement as an intentional result of investment, research, and development (R&D).

While some technological innovations may seem exogenous, such as global innovations that transform markets, most posit genuine efforts undertaken by economies and governments[3]. Factors such as investment into education and other supply-side efforts boost the long-term output of economies[4]. Additionally, providing access to technology may lead to increased access and usage of certain services. This theory is known as the innovation diffusion theory[5]. Moreover, the diffusion theory discusses concepts relating to technology's rapid adoption due to the social nature of humans. It states that at a certain adoption point, it further accelerates its adoption and increases overall economic demand. New technologies often enable new kinds of economic activity, improve efficiencies, and create new markets.

Information and communication technologies have seen rapid advancement in today's world, with their diffusion having a bidirectional relationship with economic growth and between financial sector development and economic growth in multiple countries[6]. Additionally, there is empirical evidence regarding the significant role of IT adoption in the augmentation the demand for financial services in developing regions such as the sub-Sahara[7].

India aims to leverage the economic benefits of ICT diffusion with the vision of Digital India 2030. India seeks to grow the ICT sector to $1 trillion by 2025, or 20 per cent of predicted GDP. Additionally, The Indian telecommunications sector is the second largest in the world by subscribers, with 1.2 billion wireless and fixed-line subscribers, and wireless subscriptions representing 98 per cent of telephone use[8].

A study analysing teledensity (telephones per 100 people) and economic growth delves into the intrastate findings and reveals complex nuances using empirical findings[9]. Additionally, another study used data from the telecom regulatory authority from India and saw internet broadband users as a cause for innovation, thus increasing economic growth[10]. However, it did not explore the reverse causality of economic growth increasing innovation within India. GDP may influence innovation, as economic growth provides higher disposable incomes to individuals, consequently providing resources to initiate innovation[11]. Thus, a reverse causation or a correlation may be entirely possible.

The World Bank released a report that highlights that increased broadband access tends to contribute positively to economic outputs by enhancing information accessibility, improving productivity in various sectors, and potentially creating new employment opportunities[12]. However, more studies need to delve into the state-wise granularity of internet adoption on economic growth. Additionally, current studies need to account for technology diffusion through regions and its impact on adoption.

III. Methodology:

First, we will use a regression model to analyse the impact of digital and internet infrastructure within schools on the overall usage of telecommunication devices. We can look at the individual variables and see their statistical significance in predicting outcomes, such as Wireless Users, Total Porting Requests, Wireline Users, and User Density. This data was collected through the telecom regulatory authority's subscription reports[13]. The data is by a government organisation and thus is a reputable source for official metrics and analytics. However, the data is likely skewed because the teledensity in urban areas (134.13%) is significantly higher than rural areas (58.92%). This disparity could lead to biased conclusions if the urban data disproportionately influences overall findings. Additionally, this data is self-provided by service providers and audited by the government; nonetheless, there may still be discrepancies or incentives to predict higher numbers.

1. Wireless Users: Number of individuals with a wireless broadband connection.
2. Total Porting Requests: Total number of requests by users to switch
3. Wireline Users: Number of users with fixed-line broadband connections.

Additionally, the regression model accounted for the impact of technology's existence in surrounding states. This assumption was based on the hypothesis that technology adoption diffuses through states and spreads across regions.

The data is from the Unified District Information System For Education (UDISE+) for schools' digital infrastructure and internet access. UDISE+ is one of the most extensive Management Information Systems initiated by the Department of School Education and Literacy, Ministry of Education[14]. The schools self-report the data, fed manually at the school level in the Data Capture Format (DCF) of UDISE. Essentially, school administrators are provided with a form to fill out. Hence, they may over-report statistics and be incentivised to inflate possible statistics.

Nonetheless, they have a strict reporting policy that they have to follow. Moreover, we created a dataset that told us the neighbouring digital infrastructure for each state. The neighbouring dataset was formed by seeing the neighbouring states for each state and then summing up the presence of the particular factor within the adjoining states. Lastly, the Reserve Bank of India's data was used for GDP per state (Constant Prices)[15].

OLS Regression Model

Our dependent variables will be wireless users, total porting requests, wireline users, and user density, as these outcomes will be affected by the prevalence of technological access, such as digital infrastructure and internet infrastructure in schools.

This study will see the effect of a combination of independent variables on each dependent variable.

Dependant Variables:

$$Y = Wireless\ Users,\ Total\ Porting\ Requests,\ Wireline\ Users,\ User\ Density.$$

Independent Variables:
1. GDP (Gross Domestic Product): Measure of the economic output of a region.
2. TDISR (Total Digital Infrastructure in Surrounding Regions) reflects the number of schools with computers in the surrounding states. It is used to evaluate the spill-over effect.
3. TDI (Total Computer Infrastructure): Measure the number of schools with computer access in a particular region.
4. TIISA (Total Internet Infrastructure in Surrounding Areas): Similar to TDISR but focused on Internet infrastructure.
5. ISA (Internet School Access): Number of schools with access to internet infrastructure in a given region.

First Set of Independent Variables:
GDP, Total Digital Infrastructure in Surrounding Regions (TDISR), and Total Digital Infrastructure (TDI).

Table 1: Variable Descriptions and Expected Impacts for the First Set of Independent Variables

This table lists the independent variables used in the regression model and their expected impact on telecommunication usage.

Variable	Description	Expected Impact
GDP	Economic output measure of the region.	Directly influences telecommunication usage due to economic capacity.
TDISR	Digital infrastructure in neighbouring regions.	Assesses regional spillover effects.
TDI	Total digital infrastructure within the region.	Direct measure of local digital capability and access.

$$Y = \beta 0 + \beta 1 \times GDP + \beta 2 \times TDISR + \beta 3 \times TDI + \epsilon$$

Second Set of Independent Variables:
GDP, Total Internet Infrastructure in Surrounding Areas (TIISA), and Internet School Access (ISA).

Table 2: Variable Descriptions and Expected Impacts for the Second Set of Independent Variables

This table presents the second set of independent variables focusing on internet infrastructure and their expected impacts.

Variable	Description	Expected Impact
GDP	Economic output measure of the region.	Directly influences telecommunication usage due to economic capacity.
TIISA	Internet infrastructure in neighbouring regions.	Assesses regional spillover effects.
ISA	Total internet infrastructure within the region.	Direct measure of local internet capability and access.

$$Y = \beta 0 + \beta 1 \times GDP + \beta 2 \times TIISA + \beta 3 \times ISA + \epsilon$$

These two sets of independent variables will give us insight into the availability of telecommunication and digital infrastructure in schools and its effect on telecommunication usage.

The study then shifted from assessing the impact of digital technology on telecommunication usage to the impact of higher telecommunication usage on economic activity and growth. This is bound to be a positive relationship, as higher device access will lead to more significant technology usage.

Pearson's coefficient was used to understand the statistically correlating variables, as it is an apt judge regarding the linear relationship between 2 variables. In this instance, GDP was compared to the different variables of usage: Wireless Users, Total Porting Requests, Wireline Users, and User Density.

Correlation Analysis

$$\rho GDP, X = \frac{\sum(GDPi - \underline{GDP})(Xi - \underline{X})}{\sqrt{\sum(GDPi - \underline{GDP})^2 (Xi - X)^2}}$$

Xi = Wireless_Users, Total Porting Requests, Internet School Access, GDP Per Capita (in crore), Wireline Users, User Density, Total Digital Infrastructure in Surrounding Regions, Digital Infrastructure in Schools, Total Digital Infrastructure, Telecom Towers, Total Internet Infrastructure in Surrounding Areas

After understanding each variable's statistical strength, the study aimed to find its feature significance to GDP. Consequently, it used random forests, as they provide a robust foundation for understanding variance. This machine learning model helps assess predictability.

Random Forest Through Feature Importance

Data Partitioning:

Each decision tree starts with the entire dataset and makes binary splits at each node based on a feature that minimises the residual sum of squares (RSS) across child nodes.

Splitting Criteria:

The feature chosen for splitting at each node is selected based on its ability to reduce the variance of the dependent variable (GDP in your case).

$$RSS(S) = \sum_{i \in L} (yi - \underline{y}L)^2 + \sum_{i \in R} (yi - \underline{y}R)^2$$

Feature Importance:

$$importance(Xj) = \frac{1}{M} \sum_{m=i}^{M} \Delta RSS(X_j, t_m, S_m)$$

Recursive Splitting:

The tree continues to split recursively, choosing the best feature and threshold at each node until a stopping criterion is met.

Tree Aggregation:

In the Random Forest, multiple trees are built independently.

$$\hat{y} = \frac{1}{n} \sum_{n=i}^{n} tree_m(X)$$

$$n = 100$$

This successfully gave me a foundation to understand which variables provided the best measure of predicting GDP.

However, assuming that only one variable can fully predict the variance of GDP will not provide us with an optimal output. Thus, it lead to creating an iterative algorithm to find the optimal combination of variables that gave the highest variance predictability score (R^2). This cycled through all the possible combinations of Wireless Users, Total Porting Requests, Wireline Users, and User Density. This method is known as stepwise Regression.

Step-Wise Regression

$$Y = \beta 0 + \beta i1Xi1 + \beta i2Xi2 + ... + \beta ikXik + \epsilon$$

$where\ Xi1, Xi2, ..., XikXi1, Xi2, ..., Xik\ are\ the\ variables\ that\ were\ selected\ through\ the\ stepwise\ process.$

However, it indicated a high Durbin-Watson coefficient. This showed a potential autocorrelation in the residuals, which could affect the reliability of standard errors and test statistics. Thus, we had to test the Variance Inflation Factor (VIF).

Addressing Multicollinearity using Variance Inflation Factor (VIF)

$$VIF_i = \frac{1}{1-R_i^2}$$

After removing the variable causing the multicollinearity, a Granger causality test was conducted to analyse the causality between telecommunication usage and GDP growth in the country.

The Granger causality test is assessed on a time series basis, where it sees if the change in one variable impacts another after a time lag. It's a tool to predict the change in one variable through another. It considers the impact it has on different timeframes. It measures the extent to which the past values of one variable provide valuable information for forecasting the other variable's future behaviour[16].

To understand the percentage change in Wireless Users and the Volume of UPI transactions in India, the study employed Granger causality tests to investigate whether fluctuations in wireless user percentages can predict changes in telecommunications service volume and value. Granger causality is particularly suitable for time series data, as it helps to determine whether one time series can be useful in forecasting another. This was used for time lags up to 7.

The study used data from the National Payment Corporation of India(NPCI) for economic activity. The NPCI gave data regarding the monthly value and volume of UPI Transactions[17]. At the end of the calendar year 2022, UPI's total transaction value stood at INR 125.95 trillion, up 1.75 X year-on-year (YoY), as per the NPCI. Interestingly, the total UPI transaction value accounted for nearly 86% of India's GDP in FY22[18].

Hence, the analysis assumed UPI transaction value and volume as a proxy of GDP.

Granger Test Analysis

The restricted model states that the current value of the UPI transaction volume Yt can be predicted solely from its past values. Mathematically, it is represented as

$$Yt = \alpha + \sum_{i=1}^{p} \beta_i Y_{i-1} + \epsilon_t$$

The unrestricted model extends the restricted framework by including past values of both the UPI transaction volume and the wireless user percentages, hypothesising that past values of wireless users can also predict UPI transaction volumes:

$$Yt = \alpha + \sum_{i=1}^{p} \beta_i Y_{i-1} + \sum_{i=1}^{p} \beta_i X_{i-1} + \nu_t$$

Then, to test and validate both models, the study placed the residual sum squared of the unrestricted (RSS_U) and restricted models (RSS_R). This is to test the significance of lags in the growth of each.

$$F = \frac{(RSS_R - RSS_U)/P}{RSS_U/(dfu)}$$

Additionally, also looking at another form of statistical testing known as Chi-Square:

$$\chi 2 = F \cdot (dfU)"$$

This rigorous method allowed us to test the relationship between % Change in Wireless Users and % Change in Volume of UPI transactions and % Change in Value of UPI transactions. The following steps will depict regional variances in digital infrastructure and its impact on economic processes by conducting a more nuanced analysis at the state level.

For a more granular dataset, retrieved the state-wise growth rate of % Change in Wireless Users and the district-wise statistics of approved ATM & card+PIN transactions on micro-ATMs (financial and non-financial) routed through the National Financial Service (NFS). It does not include NFS cash deposit transactions. Hence, the study used ATM transactions as a proxy for economic activity. We aggregated the district-wise statistics into a state level. All this data was monthly from April 2021 to December 2023.

Stationary Object Verification

It is critical to have the time series data stationary while performing cointegration. Stationary implies that all variables—mean, variance, and covariance—are stationary over time. Non-stationary data may reveal trends or changes in seasonality, which may adversely affect analysis.

Therefore, employing an Augmented Dickey-Fuller (ADF) Test, a widely recognised method for time-series analysis, to understand the stationary data.

$$\Delta Y_t = \alpha + \beta t + \gamma Y_{t-1} + \sum_{i=1}^{p} \delta_i \Delta Y_{t-i} + \epsilon_t$$

The ADF test operates under the following hypothesis framework:
Null Hypothesis (H0): The series has a unit root, indicating it is non-stationary.
Alternative Hypothesis (H1): The series does not have a unit root, indicating it is stationary.
If $P < 0.05$, it is stationary, and the null hypothesis is rejected.

This step ensured that the data was suitable for further testing, such as the Johansen Cointegration Testing, thus increasing the reliability of our findings.

Johansen Cointegration Test For Long-Term Equilibrium

To analyse a long-term relationship between the growth rates of economic activity and wireless users, this study utilised the Johansen Cointegration test. This test tests the long-term relationship between data and ignores short-term fluctuations and trends that may alter this relationship. Hence, this statistical method will allow the analysis to observe a consistent relationship pattern between variables. This is especially beneficial in analysing a relationship between economic variables, such as wireless user growth and ATM transaction volumes, and if they move together in the long term despite short-term fluctuations.

The Johansen Cointegration Test is conducted within the framework of a Vector Error Correction Model (VECM), given by:

$$\Delta Yt = \Pi Y_{t-1} + \sum_{i=1}^{p-1} - \Gamma_i \Delta Y_{t-i} + \epsilon_t$$

Trace Test: Tests the null hypothesis of at most r cointegrating relationships against a general alternative of n:

$$Trace\ Statistic = -T \sum_{i=r+1}^{n} log(1 - \underset{-i}{\lambda})$$

$$Maximum\ EigenVector\ Test = - Tlog(1 - \hat{\lambda}_{r+1})$$

Fitting the VECM and performing the cointegration tests—trace statistics and Maximum EigenVectorTest—allows us to see the significant long-term relationship between the variables across many time lags.

From this test, the study established a long-term equilibrium between the variables, enabling the economic interpretation and policy influences to be seen. This will help in forecasting methods. Furthermore, revealing the directional relationship between broadband wireless users and their impact on economic activity.

VECM Testing

Vector Error Correction Model (VECM) is used to analyse non-stationary co-integrated time series. We fit the model to a dataset and then perform Granger causality tests. We used the Akaike Information Criterion (AIC) to determine the optimal lag order. This method ensures that the model does not overfit.

$$AIC(p) = log|\hat{\Sigma}| + \frac{2kp}{T}$$

It evaluates the best lag order, and then we can use a vector error correction model to fit the data for the Granger causality test.

$$\Delta Yt = \mu + \Pi Y_{t-1} + \sum_{i=1}^{p-1} - \Gamma_i \Delta Y_{t-1} + \epsilon_t$$

After fitting the data, a Granger causality test was performed to understand the directionality of the policy.

This approach highlights the complex state-wise dynamics within India. It provides empirical evidence to refine and adjust the possible implementation of policies India uses to boost economic activity.

IV. Results And Discussion

The regression analysis performed in Table 3.1
First Set of Independent Variables:
1. GDP
2. Total Digital Infrastructure in Surrounding Regions
3. Total Digital Infrastructure (Access to computers in Schools)

Second Set of Independent Variables:
1. GDP
2. Total Internet Infrastructure in Surrounding Areas
3. Internet School Access

Table 3: Summary of Regression Analysis Results
This table summarises the regression analysis results, including R^2 values, coefficients, and p-values.

Variables	R^2 (First Set)	Coefficients and P-values (First Set)	R^2 (Second Set)	Coefficients and P-values (Second Set)
User Density	0.165	GDP: -1.59e-07 (0.784), TDI-SR: -1.91e-05 (0.013), TDI: -6.97e-05 (0.003)	0.015	GDP: 1.90e-07 (0.784), TII-SA: -1.11e-04 (0.071), ISA: -1.12e-03 (0.057)
Wireline Users	0.408	GDP: 0.00815 (0.002), TDI-SR: 0.0678 (0.003), TDI: -1.668 (0.001)	0.206	GDP: 0.0143 (0.002), TII-SA: -0.0214 (0.748), ISA: -21.96 (0.608)
Wireless Users	0.521	GDP: 0.407 (<0.001), TDI-SR: 17.45 (0.905), TDI: 6.24 (0.781)	0.530	GDP: 0.294 (<0.001), TII-SA: -26.19 (0.150), ISA: 458.33 (0.0001)
Total Porting Requests	0.647	GDP: 2.59e-07 (<0.001), TDI-SR: -1.18e-05 (0.103), TDI: 7.93e-06 (0.308)	0.768	GDP: 1.90e-07 (<0.001), TII-SA: 7.06e-05 (0.0015), ISA: 0.00032 (<0.001)

Regression Analysis of First Set of IVs

User density (the Number of fixed (landline) telephone connections per 100 people in a specified geographic area) seems unpredictable due to access to digital infrastructure in schools and GDP. Hence, other factors may affect the metric.

On the other hand, wireline users – those with broadband in their homes – had an explainable variance of 0.408 through GDP and other metrics. The surrounding region has a significant positive coefficient, indicating that digital infrastructure improvements are associated with increased wireline users. However, the digital infrastructure in areas leads to decreased wireline users, which is a logical fallacy. Thus, this prediction seems unfit for this model; hence, digital infrastructure in schools is a poor predictor of wireline users.

Wireless users had a R^2 of 0.521 and positive coefficients. This model suggests that digital infrastructure within schools and neighbouring regions plays a prominent role. However, the P values are high; thus, they are not statistically significant.

Total porting requests were highly predictable through GDP, with an extremely high significance below 0.001. GDP played a highly impactful role in all of these except user density. Thus, it highlights the importance of economic factors in digital telecommunications.

Overall, the presence of computers in schools does not provide substantial evidence of influencing the usage of telecommunication devices.

Regression Analysis of Second Set of IVs

User density and wireline users displayed no significant results as they had poor model fitting and low statistical significance. However, the number of wireless users was highly impacted by the access to internet infrastructure within schools, with a coefficient of 458.33 and a statistical significance of 0.0001. Hence, it highlighted that children in educational education have a massive impact on spreading internet technology throughout their households. It posits that children are adopters of technology who onboard other users onto the technology they learn in schools.

The Indian Government can create initiatives to spread internet education to children to onboard the larger population into the digital age. The porting requests are also heavily impacted by the prevalence of internet infrastructure within schools. Thus, it proves that Internet technology is consequential to the presence of wireless and wireline users.

An argument may be made that implementing internet infrastructure is only possible with children having access to computers that premise it.

The analysis of both computer infrastructure within schools and internet infrastructure allows us to analyse possible government policies to augment the usage of telecommunication infrastructure. Taking the unique route of impacting the upcoming generation posies us to affect the grassroots of households and onboard individuals through them.

According to the innovation diffusion theory, adopting new technologies should accelerate once a critical mass is reached. This aligns with our finding that increasing internet school access significantly boosts wireless usage. This suggests that schools might reach a 'critical mass' of digital literacy that spills over into community-wide technological adoption.

Next, the study aimed to analyse the economic impact of telecommunication usage.

Correlation Analysis

Table 4: Correlation Analysis

This table shows the correlation between various telecommunication and economic variables and GDP.

Variable	Correlation with GDP
GDP	1.00000
Total Porting Requests	0.73388
Wireless Users	0.69547
Internet School Access	0.66670
Wireline Users	0.44154
Total Internet Infrastructure in Surrounding Areas	0.30366
GDP Per Capita (in crore)	0.27609
Digital Infrastructure in Schools	0.03839
User Density	0.00006
Telecom Towers	-0.11128
Total Digital Infrastructure	-0.21449
Total Digital Infrastructure in Surrounding Regions	-0.25778

Total Porting requests, wireless users, and internet school access have a strong positive correlation with GDP, suggesting that these variables are related to India's GDP.

Then, we performed a random forest to see statistical significance and forecasting power.

Random Forest Test Through Feature Significance

Table 5: Random Forests Test Through Feature Significance

This table presents the significance of different features in predicting GDP as determined by the random forest model.

Feature	Importance
Wireless Users	0.32412
Total Porting Requests	0.24108

Internet School Access	0.20663
GDP Per Capita (in crore)	0.06755
Wireline Users	0.04400
User Density	0.03425
Total Digital Infrastructure in Surrounding Regions	0.02280
Digital Infrastructure in Schools	0.01913
Total Digital Infrastructure	0.01829
Telecom Towers	0.01637
Total Internet Infrastructure in Surrounding Areas	0.00579

The random forest had poor predictability, suggesting that the analysis should combine different variables to see the highest variance.

Step-Wise Regression

Table 6: Stepwise Regression

This table shows the results of the stepwise regression analysis, including coefficients, standard errors, t-statistics, p-values, and confidence intervals.

Variable	Coefficient	Standard Error	t-Statistic	p-Value	2.5% Confidence Interval	97.5% Confidence Interval
Intercept	77920	21600	3.610	0.001	34800	121000
User Density	845.4568	187.628	4.506	0.000	470.394	1220.520
Wireline Users	0.0309	0.011	2.779	0.007	0.009	0.053
Wireless Users	-0.0016	0.000	-4.601	0.000	-0.002	-0.001
Total Porting Requests	1659.0121	743.345	2.232	0.029	173.088	3144.937
Internet School Access	0.6996	0.548	1.277	0.206	-0.395	1.794

Statistic	Value
R-squared	0.760
Adjusted R-squared	0.741
F-statistic	39.33
Prob (F-statistic)	5.45e-18
Durbin-Watson	0.780
Log-Likelihood	-812.22
AIC	1636
BIC	1650
No. Observations	68
Df Residuals	62
Df Model	5

The combination of these variables gave the highest variance score of 0.760. This indicates that total porting requests are a significant predictor. However, it nullifies wireless users as they are logically highly interlinked. The higher the number of wireless users, the higher the porting requests. Thus, it is a sound reason for having a high Durbin-Watson score, which indicates autocollinearity.

Addressing Multicollinearity using Variance Inflation Factor (VIF)

Testing the variance inflation factor for the multicollinearity found these results:

Table 7: Addressing Multicollinearity using Variance Inflation Factor (VIF)

This table presents the variance inflation factor (VIF) to address multicollinearity among the variables.

Feature	VIF
Constant	20.81666
User Density	3.23715
Wireline Users	5.16880
Wireless Users	3.59441
Total Porting Requests	7.85623
Internet School Access	2.48239

A VIF score of higher than 5 suggests multicollinearity. Hence, removed total porting requests as a possible variable in the combination and tested the regression model and VIF again,

Table 8: Adjusted Stepwise Regression After VIF Adjustment

This table shows the results of the stepwise regression analysis after adjusting for multicollinearity.

Variable	Coefficient	Standard Error	t-Statistic	P-value	2.5% Confidence Interval	97.5% Confidence Interval
Intercept	88130	21800	4.052	0.000	44700	131500
User Density	679.6284	177.649	3.826	0.000	324.625	1034.632
Wireline Users	0.0459	0.009	5.039	0.000	0.028	0.064
Wireless Users	-0.0011	0.000	-3.979	0.000	-0.002	-0.001
Internet School Access	1.4535	0.444	3.271	0.002	0.565	2.342

Statistic	Value
R-squared	0.741
Adjusted R-squared	0.725
F-statistic	45.07
Prob (F-statistic)	7.99e-18
Durbin-Watson	0.654
Log-Likelihood	-814.85
AIC	1640
BIC	1651
No. Observations	68
Df Residuals	63
Df Model	4

Feature	Variance Inflation Factor(VIF)
Constant	19.880714
User Density	2.729501
Wireline Users	3.269441
Wireless Users	2.206146
Internet School Access	1.537744

User density was a significant predictor of the GDP in a state. This hypothesis was true as stated by R Kaur. User density the Number of fixed (landline) telephone connections per 100 people in a specified geographic area.

However, this study delves deeper into the impact of broadband users in India. Thus, due to the strong correlation between wireless users and GDP, the study utilises a Granger causality analysis to see the predictability of each variable to another.

Granger Causality Analysis

Table 9: Granger Causality Analysis

This table presents the results of the Granger causality analysis between wireless users and the volume and value of UPI transactions.

	Wireless Users vs Volume				Wireless Users vs Value			
Lags	F-statistic	p-value	Chi2	p-value	F-statistic	p-value	Chi2	p-value
1	0.3518	0.5580	0.3909	0.5318	0.0003	0.9861	0.0003	0.9852
2	2.4551	0.1071	5.9331	0.0515	2.5274	0.1009	6.1079	0.0472
3	3.2827	0.0410	13.1307	0.0044	3.7438	0.0268	14.9751	0.0018
4	1.2172	0.3381	7.3034	0.1207	1.8495	0.1634	11.0972	0.0255
5	1.7821	0.1771	15.4449	0.0086	3.2857	0.0335	28.4765	0.0000
6	2.4926	0.0840	31.1576	0.0000	3.2155	0.0403	40.1939	0.0000
7	1.6584	0.2353	30.9563	0.0001	5.5879	0.0101	104.3077	0.0000

Granger Causality Test: % Change in Wireless Users and % Change in Volume:

1. Lags 1 and 2: At these lags, the F-tests and p-values indicate that changes in wireless users are not statistically significant predictors of changes in volume.
2. Lag 3: Here, you see statistical significance with a p-value of 0.0410 in the F test, suggesting that changes in wireless users three months ago can predict changes in volume. The chi2 test also supports this with a p-value of 0.0044.
3. Lags 4 to 7: Statistical significance fades again, except for a somewhat notable chi2 p-value at lag 5 and 6, though corresponding F test p-values don't strongly support the hypothesis.

Granger Causality Test: % Change in Wireless Users and % Change in Value:

1. Lags 1 and 2: These initial lags show no significant predictive relationship.
2. Lag 3: Lag 3 has a strong positive predictive relationship, with the F test showing a p-value of 0.0268 and the chi2 test p-value at 0.0018. This hints that changes in wireless users can stimulate a change in value in 3 months, similar to the percentage change in volume.
3. Lags 4 to 7: Some lags, notably lag 7, show statistically solid significance (F test p-value of 0.0101 and a chi2 p-value essentially at 0.0000), suggesting a robust predictive relationship at these longer lags.

Interpretation

Volume: The relationship between changes in wireless users and changes in volume appears significant, particularly at lag 3. This indicates a delayed effect where past changes in user numbers influence volume changes after a quarter.

Value: Changes in wireless users are more consistently predictive of changes in value from lag 3, similar to volume. This suggests that it has a more prolonged response time. It also indicates a link between volume and value, as volume is likely to have a long-term impact on the value of the transactions.

A study by (author name) did a state-wise granular analysis to see the state-wise differences and understand the directionality of the relationship. There are three possible instances in each state:

Table 10: Hypothesis Types for the Relationship Between Telecommunications and Economic Growth

This table outlines the different hypothesis types regarding the relationship between telecommunications and economic growth.

Hypothesis Type	Direction	Description
Supply-led	Telecom → Growth	Suggests that telecommunications lead to economic growth.
Demand-led	Growth → Telecom	Suggests that economic growth leads to the development of telecommunications.
Feedback	Growth ↔ Telecom	Suggests a reciprocal relationship between economic growth and telecommunications development.

Neutrality	None	Suggests no relationship between telecommunications and economic growth.

This was applied to the user density hypothesis, but the same hypothesis can be applied to wireless users. A higher number of internet users can lead to economic growth or demand-led growth. As more individuals have higher incomes, the number of users will increase as people can afford more. Or it creates a feedback loop where users complement or have no relationship with each other.
To have data validity, unit root integration is used to verify the robustness and non-existence of trends.
Stationary Object Verification

Table 11: Stationary Object Verification

This table verifies the stationarity of the series using the Augmented Dickey-Fuller (ADF) test, showing each state's ADF statistic, p-value, and stationarity status.

State	Series	ADF Statistic	p-value	Is Stationary
Andhra Pradesh	Wireless User Growth	-3.643160	0.004988	True
Andhra Pradesh	% Change in NFS Volume	-2.396158	0.142824	False
Assam	Wireless User Growth	-6.448585	0.000000	True
Assam	% Change in NFS Volume	-5.168717	0.000010	True
Bihar	Wireless User Growth	-2.281416	0.178032	False
Bihar	% Change in NFS Volume	-4.796660	0.000055	True
Delhi	Wireless User Growth	-2.846552	0.051926	False
Delhi	% Change in NFS Volume	-7.309966	0.000000	True
Gujarat	Wireless User Growth	0.374950	0.980534	False
Gujarat	% Change in NFS Volume	-1.844106	0.358794	False
Haryana	Wireless User Growth	-0.765652	0.829004	False
Haryana	% Change in NFS Volume	-8.513911	0.000000	True
Himachal Pradesh	Wireless User Growth	-5.434197	0.000003	True
Himachal Pradesh	% Change in NFS Volume	-7.046308	0.000000	True
Karnataka	Wireless User Growth	-3.660296	0.004708	True
Karnataka	% Change in NFS Volume	-6.858900	0.000000	True
Kerala	Wireless User Growth	-0.771583	0.827327	False
Kerala	% Change in NFS Volume	-4.641188	0.000108	True
Madhya Pradesh	Wireless User Growth	-0.574123	0.876723	False
Madhya Pradesh	% Change in NFS Volume	-6.375554	0.000000	True
Maharashtra	Wireless User Growth	-4.007228	0.001373	True
Maharashtra	% Change in NFS Volume	-1.687653	0.437485	False
Odisha	Wireless User Growth	-3.894966	0.002072	True
Odisha	% Change in NFS Volume	-1.105576	0.712843	False
Punjab	Wireless User Growth	-1.111975	0.710273	False
Punjab	% Change in NFS Volume	-2.822426	0.051541	False
Rajasthan	Wireless User Growth	-3.222688	0.018708	True
Rajasthan	% Change in NFS Volume	-6.074539	0.000000	True
Tamil Nadu	Wireless User Growth	-4.246526	0.000549	True
Tamil Nadu	% Change in NFS Volume	-2.755854	0.064862	False
Uttar Pradesh	Wireless User Growth	-3.270656	0.016242	True
Uttar Pradesh	% Change in NFS Volume	-5.680740	0.000001	True
West Bengal	Wireless User Growth	-4.129361	0.000866	True
West Bengal	% Change in NFS Volume	-5.490241	0.000002	True

States Eligible for Cointegration Testing (where both series are stationary): Assam, Bihar (after differencing the Wireless User Growth series), Delhi, Himachal Pradesh, Karnataka, Madhya Pradesh, Rajasthan, Uttar Pradesh, West Bengal.

Johansen Cointegration Test For Long-Term Equilibrium

Table 12: Johansen Cointegration Test For Long-Term Equilibrium

This table shows the results of the Johansen cointegration test, indicating the long-term equilibrium relationship between wireless user growth and the percentage change in NFS volume for various states.

State	Eigenvalues	Trace Statistics	Max Eigen Statistics	Critical Values (90%, 95%, 99%)
Assam	[0.7012, 0.5682]	[55.30, 22.68]	[32.62, 22.68]	Trace: [13.43, 15.49, 19.93], Max: [12.30, 14.26, 18.52]
Delhi	[0.7233, 0.4295]	[49.85, 15.16]	[34.69, 15.16]	Trace: [13.43, 15.49, 19.93], Max: [12.30, 14.26, 18.52]
Himachal Pradesh	[0.6625, 0.4253]	[44.28, 14.95]	[29.33, 14.95]	Trace: [13.43, 15.49, 19.93], Max: [12.30, 14.26, 18.52]
Karnataka	[0.6409, 0.2879]	[36.82, 9.17]	[27.65, 9.17]	Trace: [13.43, 15.49, 19.93], Max: [12.30, 14.26, 18.52]
Madhya Pradesh	[0.5886, 0.2330]	[31.15, 7.16]	[23.98, 7.16]	Trace: [13.43, 15.49, 19.93], Max: [12.30, 14.26, 18.52]
Rajasthan	[0.6334, 0.3021]	[36.81, 9.71]	[27.10, 9.71]	Trace: [13.43, 15.49, 19.93], Max: [12.30, 14.26, 18.52]
Uttar Pradesh	[0.4555, 0.2051]	[22.61, 6.20]	[16.41, 6.20]	Trace: [13.43, 15.49, 19.93], Max: [12.30, 14.26, 18.52]
West Bengal	[0.8918, 0.3553]	[71.91, 11.85]	[60.05, 11.85]	Trace: [13.43, 15.49, 19.93], Max: [12.30, 14.26, 18.52]

For most states, the trace and max eigen statistics for at least one cointegration relationship exceed the critical values at the 95% significance level, suggesting at least one cointegration equation among the series. This implies a long-term equilibrium relationship between wireless user growth and the percentage change in NFS volume despite short-term fluctuations.

1. West Bengal displayed evidence of cointegration with a high significance, thus showing the possibility of multiple cointegration relationships.
2. Delhi and Himachal Pradesh also show strong cointegration evidence, with significant trace and max eigen statistics.
3. Madhya Pradesh and Uttar Pradesh present weaker cointegration cases than others, as their lower trace and max eigen statistics indicate. However, they still suggest at least one cointegrating relationship at the 95% significance level.

Conclusions:

The Johansen cointegration tests indicate that for the states analysed, there is evidence to suggest a long-term relationship between wireless user growth and the percentage change in NFS volume. Thus, it displays that the monthly trends of both economic variables follow a long-term relationship.

Testing The Directionality Of Change in Wireless Users and Change in Economic Growth

Table 13: Testing The Directionality Of Change in Wireless Users and Change in Economic Growth

This table details the results of the Granger causality tests to determine the directionality of the relationship between wireless user changes and economic growth across different states.

State	Granger Causality Test	Result	Test Statistic	Critical Value	P-value	Degrees of Freedom
Assam	% Change in NFS Volume → Wireless User Growth	Reject H0	15.56	3.500	0.000	(7, 8)

	Wireless User Growth → % Change in NFS Volume	Reject H0	8.211	3.500	0.004	(7, 8)
Delhi	% Change in NFS Volume → Wireless User Growth	Reject H0	4.203	3.500	0.031	(7, 8)
	Wireless User Growth → % Change in NFS Volume	Reject H0	23.39	3.500	0.000	(7, 8)
Himachal Pradesh	% Change in NFS Volume → Wireless User Growth	Reject H0	3.970	3.500	0.036	(7, 8)
	Wireless User Growth → % Change in NFS Volume	Fail to reject H0	2.921	3.500	0.078	(7, 8)
Karnataka	% Change in NFS Volume → Wireless User Growth	Reject H0	19.90	3.500	0.000	(7, 8)
	Wireless User Growth → % Change in NFS Volume	Reject H0	4.711	3.500	0.022	(7, 8)
Madhya Pradesh	% Change in NFS Volume → Wireless User Growth	Reject H0	4.281	3.500	0.029	(7, 8)
	Wireless User Growth → % Change in NFS Volume	Reject H0	8.370	3.500	0.004	(7, 8)
Rajasthan	% Change in NFS Volume → Wireless User Growth	Reject H0	6.095	3.500	0.010	(7, 8)
	Wireless User Growth → % Change in NFS Volume	Fail to reject H0	1.969	3.500	0.181	(7, 8)
Uttar Pradesh	% Change in NFS Volume → Wireless User Growth	Reject H0	9.700	2.848	0.000	(6, 14)
	Wireless User Growth → % Change in NFS Volume	Fail to reject H0	1.455	2.848	0.263	(6, 14)
West Bengal	% Change in NFS Volume → Wireless User Growth	Fail to reject H0	0.1006	4.062	0.753	(1, 44)
	Wireless User Growth → % Change in NFS Volume	Fail to reject H0	3.398	4.062	0.072	(1, 44)

Assam, Karnataka, Madhya Pradesh, and Uttar Pradesh exhibit bilateral causality, indicating that changes in NFS Volume and Wireless User Growth significantly predict each other. This mutual causality suggests a dynamic interplay where the growth in wireless users and changes in NFS transactions drive each other, potentially indicating a symbiotic relationship between technological adoption and financial activity in these states. This logically makes sense as higher technological adoption leads to higher digital financial transactions, and increased economic activity leads to higher spending and incomes for individuals. Thus, individuals can afford to adopt technological advancements like the Internet,

Delhi shows that both "% Change in NFS Volume" and "Wireless User Growth" significantly cause each other, reinforcing the closely tied relationship between digital connectivity and financial transactions. Additionally, this can be attributed to the fact that Delhi is a highly well-connected metropolitan city.

Himachal Pradesh presents a case where "% Change in NFS Volume" significantly Granger-causes "Wireless User Growth," but the reverse causality from "Wireless User Growth" to "% Change in NFS Volume" is not significant. This may suggest that changes in financial transactions or activities might precede and predict changes in wireless user growth in this state. It may also indicate that government policy needs to be readjusted so that more internet users can impact financial transactions.

Rajasthan shows significant causality from "% Change in NFS Volume" to "Wireless User Growth," but not the other way around, similar to Himachal Pradesh, suggesting a directional influence of financial activities on technological growth.

West Bengal presents an interesting case where neither of the series significantly Granger causes the other at the conventional 5% significance level, hinting at potential other factors or external influences driving changes in wireless user growth and NFS transactions that this model does not capture.

In line with Solow's model, which suggests that technological advancements drive economic growth independently of traditional inputs, our findings reveal that increases in internet users robustly predict improvements in GDP per capita across various states. As previously stated, the growth of internet users can be attributed to the rise in internet access in schools. Hence, it can be assumed that giving children access to digital technology with internet capabilities can augment technological adoption and boost economic growth.

Additionally, consistent with predictions made from the World Bank's assertions on ICT benefits, Granger's analysis confirms that enhanced digital access facilitates increases in economic output, thereby supporting the hypothesised benefits of ICT proliferation detailed by the World Bank report.

Detailed Recommendations Found Through Research:

1. Targeted Digital Infrastructure In Schools: Internet and Digital infrastructure in schools boost the adoption of digital technology throughout India. This is an underserved area, and the government could provide funding to schools and educational centres to give children access. This not only has the long-term benefit of building lasting skills within the children through technology, but the analysis uncovered that it has a short-term impact on adoption in their households. As early adopters of technology, children can be a catalyst to bolster the digital India 2030 initiative. Additionally, educating them about skills such as internet banking or digital payments will likely spill over to their households.
2. Data-Driven Expansion of Telecommunication Networks: The study's regression model showed that regions have a geographical spill-over effect to adjacent regions. The government of India can prioritise expansion in underserved areas with higher populations. Targeting key central regions such as Uttar Pradesh, Maharashtra, Kartaka, West Bengal and Rajhasthan can be highly beneficial as they can be critical pathways into a country-wide digital adoption.
3. Capacity Building and Digital Literacy Programs: Develop comprehensive curricula to engage students in participating in the digital economy. Enhancing digital literacy will increase the use of existing digital infrastructure and empower citizens to participate more fully in the digital economy, leading to increased economic activity and development.

State Specific Reccomendations:
States that show bilateral causality:

1. Digital and Financial Inclusion Programs: A combination of digital and financial programs will prove beneficial, as they have a cyclical relationship. Due to this mutual reinforcement, it is vital to have affordable programs in this field.
2. Entrepreneurship and Innovation Support: Supporting entrepreneurs in developing new financial and digital technologies will help foster both aspects of the economy, leading to higher economic activity and growth in the region.

Delhi In Specific:

1. Public-Private Partnerships (PPP): Encourage PPP models to expand and upgrade existing digital infrastructure, focusing on sustainability and innovation. Additionally, a focus on building sustainable cities is vital as they are highly user-dense cities.

Unilateral Causality:

1. Focus on Financial Services Development: Since financial growth seems to precede wireless growth, policies should prioritise enhancing the financial services sector, possibly through improved banking services accessibility in rural and underserved areas.
2. Digital Outreach Programs: Implement targeted digital outreach and education programs in less connected areas to facilitate a better understanding and adoption of technology following improvements in financial conditions. Need to understand why individuals in that region do not utilise financial services despite being onboarded to the digital world.

V. Conclusion:

This research paper has explored the insightful relationship between telecommunication and economic growth and activity within an enterprising country like India. Various statistical models such as regression analysis, correlation tests, and causality models identified a clear and robust link between enhanced digital access and the facilitation of economic inclusion and financial activity in an economy. Additionally, finding a unique link between internet access in educational institutions and economic growth within an economy.

The findings underscore the critical impact of digital infrastructure in schools. India can enable children to create new generational trends within their families and significantly impact the 2030 Digital India initiative. We foster a generational shift in digital literacy and usage patterns by enabling children, the early adopters, to access digital technologies. The geographical spill-over effect observed indicates that benefits in one region can extend to neighbouring areas, further amplifying the positive impact of digital infrastructure investments.

The study also highlights the complex, bidirectional relationships between telecommunications development and economic growth, suggesting that these influences vary significantly between states. For example, in regions such as Assam and Karnataka, the interaction between telecommunications and economic activity is mutually reinforcing. In contrast, in places like Rajhastan, there needs to be an emphasis on particular variables and policies.

Additionally, the study provided policy recommendations based on the results of robust econometrics testing. Suggesting that investment in rural areas toward digital literacy and financial inclusion programs will augment and serve as a catalyst for the vision that India possesses.

For future research, looking at a more extended dataset of more than three years is suggested, as limited data is available due to the recency in state-wise UPI data recordings. Looking at longer relationships between internet adoption and financial activity will be an important factor and can reveal new relationships between the economic variables. This study would be more robust if data validity were higher and more states passed the unit root test.

In conclusion, as India continues to enhance its digital infrastructure, it is set to reap significant economic benefits. The findings of this study provide a compelling case for continued and focused investment in digital technologies at the grassroots level. This will ensure the continued development of the country.

Glossary

Augmented Dickey-Fuller (ADF) Test:

- A statistical test is used to determine whether a time series is stationary. It tests for the presence of a unit root, which would indicate non-stationarity.

Cointegration:

- A statistical property of time series variables is that if two or more series are individually non-stationary, their linear combination may still be stationary. This suggests a long-term equilibrium relationship among them.

Confidence Interval:

- A range of values derived from the sample data is likely to contain the value of an unknown population parameter. The wider the interval, the higher the confidence in containing the actual parameter.

Correlation Analysis:

- A method used to measure the strength and direction of a linear relationship between two random variables.

Dependent Variable:

- A variable is studied to see if and how it responds to changes in another variable (the independent variable).

Effect Size:

- A quantitative measure of the strength of a phenomenon. Examples include "r" for correlation coefficients or "d" for differences between group means.

Granger Causality Test:

- A statistical hypothesis test determines whether a one-time series can be used to forecast another.

Independent Variables:

- Variables that are manipulated or categorised to determine if they affect the dependent variable.

Johansen Cointegration Test:

- A procedure for testing the cointegration relationships between several non-stationary time series.

Multiple Testing Correction:

- Procedures adjust the significance levels of individual tests when multiple statistical tests are conducted simultaneously, reducing the chance of erroneous inferences.

OLS (Ordinary Least Squares) Regression Model:

- A method for estimating the unknown parameters in a linear regression model to minimise the differences between the observed responses and the responses predicted by the linear approximation.

Pearson's Coefficient:

- A measure of the linear correlation between two variables, giving a value between -1 and 1 where 1 is total positive linear correlation, 0 is no linear correlation, and -1 is total negative linear correlation.

Random Forest:

- An ensemble learning method for classification, regression, and other tasks operates by constructing many decision trees at training time and outputting the class, which is the mode of the classes (classification) or mean prediction (regression) of the individual trees.

RSS (Residual Sum of Squares):

- A measure of the discrepancy between the data and an estimation model. A smaller RSS indicates a better fit of the model to the data.

Stepwise Regression:

- A method of fitting regression models is one in which an automatic procedure chooses predictive variables.

Vector Error Correction Model (VECM):

- A multivariate model is used to analyse cointegrated time series data, which includes long-term and short-term dynamics. The error correction term derived from the cointegration relationships ensures that the variables return to a long-term equilibrium.

Variance Inflation Factor (VIF):

- A measure of the amount of multicollinearity in an ordinary least squares regression analysis. It provides an index that measures how much the variance of an estimated regression coefficient is increased because of collinearity.

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