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Article

India’s digital public infrastructure: Analyzing UPI and Aadhaar in GDP growth and cost optimization

Aniket Thukral[1], Lakshit Dagar[2]

[1] Heritage International Xperiential School, Gurugram, Haryana, India

[2] JD Sports Fashion, Manchester, England, United Kingdom

SUMMARY

India's Digital Public Infrastructure (DPI) has gained global recognition, with institutions like the International Monetary Fund (IMF) and the Group of Twenty (G20) (IMF) endorsing its model for financial inclusion and public service delivery. DPI comprises the Unified Payments Interface (UPI), a real-time payments network, and Aadhaar, a biometric ID system for identity verification. Together, they provide a scalable framework for economic empowerment and governance efficiency. This study quantifies their macroeconomic impact, hypothesizing that UPI contributes to Gross Domestic Product (GDP) growth primarily through reduced transaction costs, while Aadhaar supports GDP growth through Direct Benefit Transfer (DBT) efficiencies. We conducted regression analyses over an eight-year period (2016–17 to 2023–24): estimating GDP growth as a function of UPI transaction value, Aadhaar authentication volumes, and Aadhaar Enabled Payment Services (AePS) transaction value, controlling for macroeconomic factors such as unemployment (for labor market fluctuations), government spending (to capture fiscal policy effects), and internet penetration (as a prerequisite for DPI usage). Findings indicate that, on average, UPI contributed an amount equivalent to 3.4% of India’s annual GDP, while Aadhaar’s impact ranged between 2.5% and 4.3% of annual GDP, based on authentication volumes and AePS transaction value, respectively. All effects were statistically significant at the 5% level, with 95% confidence intervals excluding zero. A further analysis compared UPI’s cost savings with cash and cards and assessed Aadhaar-enabled DBT efficiencies. These results underscore DPI’s role as a macroeconomic growth catalyst, emphasizing the need for sustained investment and targeted policy measures to expand its scalability and long-term impact.

INTRODUCTION

Digital transformation is driving global economic change, with Digital Public Infrastructure (DPI) emerging as a cornerstone for economic growth, financial inclusion, and public service efficiency (1). Recognized by the United Nations as one of its 12 High Impact Initiatives, DPI is positioned to catalyze collective action, supporting its implementation and adoption in over 100 countries (2). DPI streamlines government operations, enhances public service delivery, and fosters socioeconomic opportunities, making it a vital tool for global development (3). The COVID-19 pandemic further underscored the importance of robust DPI, with countries having strong DPI reaching 51% of their populations through digital payments, compared to just 16% in others (3). A study by McKinsey Global Institute estimates that digital ID systems alone could unlock economic value equivalent to 3–13% of Gross Domestic Product (GDP), with an average 6% improvement for emerging economies (4).

Among these emerging economies, India stands out as a global pioneer in DPI implementation. Its ecosystem has garnered widespread international acclaim, with institutions such as the International Monetary Fund (IMF), World Bank, and the Group of Twenty (G20) recognizing it as a replicable model for digital transformation (5). The World Bank highlighted India’s Jan Dhan, Aadhaar, Mobile (JAM) trinity as a key driver behind financial inclusion rates rising from 25% in 2008 to over 80% in recent years, a process that could have otherwise taken up to 47 years (6). India’s DPI has also fueled a digital payments revolution, with the country accounting for 49% of global real-time payment transactions in 2023 (7). Leading this transformation, UPI recorded 129.3 billion transactions out of a global total of 266.2 billion, according to ACI Worldwide’s 2024 report (7). This marks a remarkable shift for a nation that, until recently, conducted 90% of its transactions in cash (8). At the core of India’s DPI success are two foundational systems: a) Aadhaar: A biometric ID system covering 1.37 billion Indian citizens (97% of the population) since its inception in 2010 and b) UPI: A real-time payments network that remains the cornerstone of India’s digital payments ecosystem, growing from 920 million transactions in FY 2017–18 to 13,116 million in FY 2023–24 (a Compound Annual Growth Rate of 129%) (9,10). Beyond its economic value, DPI provides financial benefits, ecological advantages, and process efficiencies for citizens. Despite its widespread adoption and global relevance, there remains limited empirical research quantifying DPI’s direct macroeconomic impact, particularly on GDP growth. This gap stems from several factors. First, the nationwide adoption of DPI systems such as Aadhaar and UPI is relatively recent, and their gradual scale-up over the last decade has only recently generated sufficient data coverage. Second, there is an absence of long-term, publicly available datasets. A further challenge is the lack of standardized methodologies linking DPI metrics with national economic indicators. Existing studies have largely focused on financial inclusion or transaction-level efficiencies, often through case studies or single-year estimates. For example, a survey-based study by the World Economic Forum examined UPI’s cost savings but didn’t link these savings to GDP growth (11). Similarly, the National Association of Software and

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Year	Dependent (Y)	Independent (X)				
	GDP	Key Variable		Control Variables		
		X1		X2	X3	X4
		UPI Transactions Value		Government Spending	India Unemployment Rate[1]	Internet Penetration Rate[2]
	in ₹trillions	in ₹millions	Min-Max Scaled	% of GDP	%	%
2016-17	160	69,521	0.000	0.128	0.078	0.165
2017-18	171	1,098,318	0.005	0.125	0.077	0.240
2018-19	189	8,769,000	0.044	0.123	0.077	0.285
2019-20	201	21,320,000	0.106	0.134	0.065	0.337
2020-21	199	41,040,000	0.205	0.177	0.079	0.434
2021-22	236	84,000,000	0.420	0.160	0.064	0.463
2022-23	269	139,210,000	0.696	0.154	0.048	0.481
2023-24	295	199,860,000	1.000	0.149	0.042	0.515

Table 1: Data inputs for regression of Gross Domestic Product (GDP) and Unified Payments Interface (UPI) transactions, 2016–17 to 2023–24. Annual values of India's Gross Domestic Product (₹trillions) and Unified Payments Interface transaction values, the key independent variable (₹millions, also shown in min-max scaled form). Control variables include government spending as a share of GDP, unemployment rate, and internet penetration. Data sources: RBI (13), NPCI (14), Trading Economics (15), Macrotrends (16), Statista (17).

Service Companies (NASSCOM), in collaboration with Arthur D. Little, released a report titled "Digital Public Infrastructure of India – Accelerating India's Digital Inclusion", which estimated DPI's value-creation at ~0.9% of India's GDP in 2022 but focused on a single year without detailing its methodology (12). In contrast, our study adopts a more empirical approach, analyzing both Aadhaar and UPI over an eight-year period (2016–17 to 2023–24) using multiple regression models and cost-saving analyses to evaluate their impact on GDP growth. This timeframe was selected because 2016 marks the year UPI was launched and Aadhaar enrollments surpassed one billion, covering the majority of India's ~1.3 billion population. This provided a clear starting point for DPI's large-scale implementation, while 2023 represents the most recent year for which complete data were available at the time of analysis. We hypothesize that Aadhaar and UPI contribute significantly to GDP, with transaction cost reductions through UPI serving as the primary driver of economic benefits, while Direct Benefit Transfer (DBT) savings via Aadhaar enhances overall efficiency by reducing leakages and eliminating ghost beneficiaries. To assess Aadhaar's economic impact, we employed two models: one using Aadhaar Net Authentications and another using Aadhaar Enabled Payment Services (AePS) transaction volume. Aadhaar Net Authentications refer to the number of successful identity verifications conducted through the Aadhaar system, including biometric and OTP-based transactions used across sectors such as banking, welfare, and telecom. AePS transaction volume captures the total number of Aadhaar-enabled financial transactions, such as cash withdrawals, fund transfers, and balance checks, facilitated through micro-ATMs or banking correspondents. Our analysis estimated that, over the eight-year review period, UPI contributed ₹58.43 trillion to GDP, accounting for an average annual share of 3.39%. Aadhaar's estimated contribution ranged from ₹43.46 trillion (AePS model) to ₹73.94 trillion (authentications model), corresponding to annual averages of 2.5% to 4.3%. Combined cost savings from UPI transaction efficiencies and DBT reforms amounted to ₹15.42 trillion.

By quantifying Aadhaar and UPI's economic impact through empirical analysis, our study provides a structured framework for policymakers and global economies to leverage DPI for sustained macroeconomic growth and financial inclusion. Our findings also identified AePS as a notable offshoot of Aadhaar, with strong direct linkages to GDP growth, particularly in rural and unbanked areas. However, AePS transactions saw a slight decline in 2023–24, dropping from ₹1,258.20 million to 1,197.05 million, with extrapolated data for FY 2024–25 projecting a continued downward trend to ₹1189.32 million. Whether this decline is a temporary fluctuation or signals a broader structural shift requires further investigation at the policy level. Strengthening AePS adoption will be crucial for sustaining its impact and ensuring continued financial inclusion in underserved regions.

RESULTS

UPI's contribution to GDP growth

As UPI accounts for over 80% of digital retail payments in India and is projected to reach 91% by FY 2028–29, we analyzed its direct impact on GDP. A multiple regression analysis was conducted with GDP growth as the dependent variable and UPI transaction value as the key independent variable, controlling for unemployment (percentage of the labor force without jobs), government spending (public expenditure as a percentage of GDP), and internet penetration (share of the population with internet access) (**Table 1**). The model is specified as:

$$GDP_t = \beta_0 + \beta_1 UPI_t + \beta_2 GovExp_t + \beta_3 UnempRate_t + \beta_4 InternetPen_t + \varepsilon$$

where GDP_t represents growth at time t, β_0 is the regression intercept, β_1, β_2, β_3, β_4 are the estimated coefficients capturing the marginal effect of UPI transactions, government expenditure, unemployment rate, and internet penetration (as defined above) on GDP growth; and ε is the error term that captures unobserved macroeconomic and institutional factors not included in the model.

The regression results indicated a significant relationship between UPI transactions and GDP growth, with a coefficient of 58.43 and a p-value of 0.0277 (**Table 1**). Because UPI transaction values were min-max scaled between 0 and 1, this coefficient reflects the GDP change associated with the observed increase of about ₹199.8 trillion in UPI transactions

Year	Dependent (Y)	Independent (X)			
	GDP	Key Variable		Control Variables	
		X1		X2	X3
		Aadhaar Net Authentications[3]		Government Spending, (4-Year Lag, %GDP)[4]	India Unemployment Rate
	in ₹trillions	in millions	Min-Max Scaled	% of GDP	%
2016-17	160	4,036	0.000	0.142	0.078
2017-18	171	12,619	0.314	0.139	0.077
2018-19	189	10,805	0.247	0.133	0.077
2019-20	201	11,135	0.259	0.130	0.065
2020-21	199	14,134	0.369	0.128	0.079
2021-22	236	17,710	0.500	0.125	0.064
2022-23	269	22,920	0.690	0.123	0.048
2023-24	295	31,403	1.000	0.134	0.042

Table 2: Table 2: Data inputs for regression of Gross Domestic Product (GDP) and Aadhaar authentications, 2016–17 to 2023–24. Annual values of India's Gross Domestic Product (₹trillions) and Aadhaar net authentications, the key independent variable (millions, also shown in min-max scaled form). Control variables include government spending as a share of GDP (applied with a four-year lag) and unemployment rate. Data sources: RBI (13), UIDAI (9), Trading Economics (15), Macrotrends (16).

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(from ₹0.07 trillion in 2016–17 to ₹199.9 trillion in 2023–24), corresponding to an estimated rise of about ₹58.4 trillion. The model showed high explanatory power (R^2 = 0.9978, Adjusted R^2 = 0.9948), reinforcing UPI's role in economic expansion through transaction efficiency. However, methodological limitations warrant caution. Macroeconomic regressions are inherently vulnerable to issues such as autocorrelation, omitted variable bias, and endogeneity, particularly given the short eight-year dataset. Unobserved factors like policy shifts, global shocks, or concurrent structural reforms could influence both UPI adoption and GDP growth. To mitigate these risks, we included key control variables (unemployment rate, government spending, and internet penetration) and tested alternative model specifications by removing one control at a time to assess coefficient stability. These sensitivity checks yielded consistent signs and significance levels. We also conducted residual diagnostics, including the Durbin-Watson (DW) test, autocorrelation function (ACF), and heteroskedasticity tests. These diagnostics indicated no major model failures. Internet penetration also exhibited a statistically significant effect on GDP growth (p = 0.0124), aligning with its role in enabling digital payments.

Aadhaar authentication and GDP correlation

While UPI drives digital transactions, Aadhaar anchors financial inclusion through secure identity verification and banking access. To assess its macroeconomic impact, we conducted a regression analysis examining GDP growth as a function of Aadhaar authentication volumes, controlling for unemployment and lagged government spending (public expenditure as a percentage of GDP lagged by four years) (**Table 2**). The model is specified as:

$$GDP_t = \beta_0 + \beta_1 Aadhar_t + \beta_2 GovExp_t + \beta_3 UnempRate_t + \varepsilon$$

where GDP_t represents growth at time t, β_0 is the regression intercept, β_1, β_2, β_3 are the estimated coefficients capturing the marginal effect of Aadhaar authentication volumes, government expenditure, and unemployment rate (as defined above) on GDP growth; and ε is the error term that captures unobserved macroeconomic and institutional factors not included in the model.

The regression results indicated a strong correlation between Aadhaar authentication volumes and GDP growth, with a coefficient of 73.94 and a p-value of 0.0263 (**Table 2**). Because Aadhaar authentication volumes were min-max scaled between 0 and 1, this coefficient reflects the GDP change associated with the observed increase of about 27.4 billion in Aadhaar authentication volumes (from about 4 billion in 2016–17 to 31.4 billion in 2023–24), corresponding to an estimated rise of about ₹73.94 trillion. The model exhibited high explanatory power (R^2 = 0.9847, Adjusted R^2 = 0.9732), supporting Aadhaar's role in economic participation through secure transactions and financial inclusion. Additionally, lagged government spending (% of GDP) yielded a negative coefficient (-1195.26, p = 0.0827), while unemployment proved statistically significant (-1504.96, p = 0.0300). As Aadhaar functions as a structural policy platform influencing welfare delivery, financial inclusion, administrative efficiency, and several other factors, endogeneity (where explanatory variables are correlated with the error term, potentially biasing estimates) and omitted variable bias (arising when important explanatory factors are excluded from the model) remain relevant concerns. The robustness checks and alternative specifications conducted for the UPI model were similarly applied here.

Aadhaar-linked financial transactions: AePS and GDP

Aadhaar authentication volumes indicate financial inclusion, but their direct impact on GDP is less immediate. To assess a more direct economic contribution, we introduced AePS transaction volume as an alternative independent variable, incorporating unemployment and lagged government spending (public expenditure as a percentage of GDP lagged by two years) as control variables (**Table 3**). The model is specified as:

$$GDP_t = \beta_0 + \beta_1 AePS_t + \beta_2 GovExp_t + \beta_3 UnempRate_t + \varepsilon$$

where GDP_t represents growth at time t, β_0 is the regression intercept, β_1, β_2, β_3 are the estimated coefficients capturing the marginal effect of AePS transaction volumes, government expenditure, and unemployment rate (as defined above) on GDP growth; and ε is the error term that captures unobserved macroeconomic and institutional factors not included in the model.

The regression results indicated a statistically significant relationship between AePS transaction volume and GDP growth, with a coefficient of 45.71 and a p-value of 0.0201 **(Table 3).** Because AePS transaction volumes were min-

Year	Dependent (Y)	Independent (X)			
		Key Variable		Control Variables	
		X1		X2	X3
	GDP	AePS Transactions Volume[5]		Government Spending, (2-Year Lag, %GDP)[6]	India Unemployment Rate
	in ₹trillions	in millions	Min-Max Scaled	% of GDP	%
2016-17	160	16	0.000	0.133	0.078
2017-18	171	106	0.072	0.130	0.077
2018-19	189	254	0.192	0.128	0.077
2019-20	201	437	0.339	0.125	0.065
2020-21	199	963	0.763	0.123	0.079
2021-22	236	1,111	0.881	0.134	0.064
2022-23	269	1,258	1.000	0.177	0.048
2023-24	295	1,197	0.951	0.160	0.042

Table 3: Data inputs for regression of Gross Domestic Product (GDP) and Aadhaar-enabled Payment System (AePS) transactions, 2016–17 to 2023–24. Annual values of India's Gross Domestic Product (₹trillions) and Aadhaar-enabled Payment System transaction volumes, the key independent variable (millions, also shown in min–max scaled form). Control variables include government spending as a share of GDP (applied with a two-year lag) and unemployment rate. Data sources: RBI (13), NPCI (18), Trading Economics (15), Macrotrends (16).

Payment Method	Average Cost Per Transaction (₹)	Cost Type
UPI	₹0.0025 per ₹1 transaction	Digital Processing
Debit Cards	₹12.24 per ₹1700 transaction	Merchant Discount Rate (MDR) + Bank Fees
Credit Cards	1.5%–2.5% of transaction value	MDR + Bank Fees + Interest
Cash Withdrawals	₹20– ₹25 per ATM withdrawal	Bank + Cash Handling

Table 4: Comparison of Transaction Costs Across Payment Methods. Average costs per transaction for Unified Payments Interface (UPI), debit cards, credit cards, and cash withdrawals. Values are shown in Indian rupees, with cost type indicating the primary components of each transaction cost. Data sources: RBI (19, 21) and industry reports.

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Year	UPI Transactions Value (₹ M)	Transaction Cost Savings (₹ M)	Estimated Contribution to GDP (₹ T)
2016-17	69,520	356	-
2017-18	1,098,320	22,155	0.3
2018-19	8,769,000	122,242	2.24
2019-20	21,320,000	284,910	3.67
2020-21	41,040,000	553,353	5.77
2021-22	84,000,000	1,383,061	12.56
2022-23	139,210,000	3,048,576	16.15
2023-24	199,860,000	5,872,792	17.74

Table 5: UPI Transaction Cost Savings and Estimated GDP Contribution, 2016–17 to 2023–24.
Annual values of UPI transactions (₹millions), estimated cost savings relative to traditional payment methods (cash and cards, ₹millions), and the portion of GDP (₹trillions) attributed to these efficiency gains, derived using regression-adjusted scaling of transaction volumes. Data sources: RBI Statistics (19, 20).

Year	Total DBT Transfers (₹ M)	Estimated DBT Savings (₹ M)	% of Transfers Saved
2016-17	3,10,000	77,668	25.10%
2017-18	9,00,000	225,489	25.10%
2018-19	13,90,000	348,255	25.10%
2019-20	24,60,000	616,337	25.10%
2020-21	28,90,000	724,070	25.10%
2021-22	31,40,000	786,706	25.10%
2022-23	32,90,000	636,969	19.40%
2023-24	33,40,000	715,915	21.40%

Table 6: Aadhaar-Enabled DBT Transfers and Estimated Savings from Leakage Reduction, 2016–17 to 2023–24. Annual values of Aadhaar-enabled Direct Benefit Transfers (DBT, ₹millions), estimated savings from reduced subsidy leakages (₹millions), and the share of transfers saved (%). Savings were estimated from cumulative government-reported DBT data. Data sources: DBT Bharat and Ministry of Finance (22, 23).

max scaled between 0 and 1, this coefficient reflects the GDP change associated with the observed increase of about 1,181 million in AePS transaction volumes (from about 16 million in 2016–17 to 1,197 million in 2023–24), corresponding to an estimated rise of about ₹45.71 trillion. Compared to Aadhaar authentication volumes, this model established a stronger direct linkage to GDP, as AePS reflects actual financial transactions rather than identity verification alone (R^2 = 0.9799, Adjusted R^2 = 0.9649). However, given AePS's overlap with both Aadhaar infrastructure and UPI-led payment growth, risks of endogeneity and omitted variables as stated above apply.

All three models, including AePS, exhibited high explanatory power ($R^2 > 0.97$), which raises the possibility of overfitting, particularly given the limited number of observations. However, residual plots, heteroskedasticity tests, and other diagnostics did not indicate model failure. While these checks reinforce internal consistency, the results should still be interpreted as preliminary and with caution, particularly because the limited timeframe may not fully capture the longer-term effects of Aadhaar's and UPI's gradual adoption.

UPI cost savings and GDP contribution

Beyond regression estimates, we further analyzed UPI's macroeconomic impact by quantifying cost savings from digital payment efficiencies through a two-step approach. First, we compared UPI's transaction costs with traditional methods, such as cash withdrawals (₹20–₹25 per transaction) and card payments (1.5%–2.5% of transaction value), finding UPI to be the most cost-efficient at ₹0.0025 per ₹1 transacted (**Table 4**). These estimates were sourced from Reserve Bank of India (RBI) discussion papers, National Payments Corporation of India (NPCI) datasets, and public financial institution disclosures. Applying these rates to annual transaction volumes, we calculated total savings increasing from ₹356 million in FY 2016–17 to ₹5.87 trillion in FY 2023–24 (**Table 5**). Second, to assess UPI's broader contribution to GDP via cost efficiency, we normalized UPI transaction values using min-max scaling and applied the change over time to the coefficient (₹58.43 trillion) from our main UPI-GDP regression model. This yielded a directional estimate of GDP contribution rising from ₹0.30 trillion in FY 2017–18 to ₹17.74 trillion in FY 2023–24. While this approach estimates a direct relationship via transaction efficiency, secondary effects, such as increased consumer spending or business reinvestment, are not modeled but may amplify the actual economic benefit.

Aadhaar-enabled DBT savings

Where UPI drives transaction efficiency, Aadhaar strengthens fiscal management by reducing subsidy leakages in the DBT system. However, its broader macroeconomic contribution is less directly measurable than transaction-based metrics like AePS. To bridge this gap, we analyzed Aadhaar-enabled DBT savings to quantify its role in improving fiscal management and subsidy efficiency. Between FY 2016–17 and FY 2023–24, DBT transfers increased from ₹0.31T to ₹3.34T, with estimated savings from reduced leakages ranging from ₹0.078T to ₹0.72T (**Table 6**).

DISCUSSION

Our study reveals that India's DPI, particularly UPI and Aadhaar, plays a pivotal role in shaping the country's economic landscape. The regression analysis indicated that UPI transactions have a statistically significant positive effect on GDP growth (p = 0.0277), underscoring the potential of digital payments to enhance financial inclusion and economic efficiency. Internet penetration also demonstrated a statistically significant relationship with GDP growth (p = 0.0124), reinforcing its role in enabling digital financial services, e-commerce, and financial inclusion.

We recognize the potential for multicollinearity between UPI transactions and internet penetration, which may obscure UPI's independent effect on GDP. Although we did not conduct formal Variance Inflation Factor analysis due to the limited eight-year dataset (2016–2024), we addressed this risk through careful variable selection. Specifically, we included only one representative indicator for each macroeconomic domain, for example, internet penetration for digital access, government spending for fiscal policy, and unemployment for labor market health. This helped minimize functional overlap and ensured each variable added distinct explanatory value.

To strengthen model reliability despite the short time series, we performed diagnostic tests including residual analysis, heteroskedasticity checks, and alternative model specifications. Coefficient signs and significance levels remained stable, reinforcing the internal consistency of our findings.

The model holds even when accounting for the COVID-19 pandemic outlier, where GDP declined while UPI transactions surged. UPI transaction volumes continued to rise even after the closing of the COVID-19 pandemic, indicating a structural shift toward digital payments as consumers and businesses moved away from cash. While this suggests a long-term trend, further research is needed to assess whether the acceleration effect persists in the post-pandemic economy. Furthermore, since UPI was only introduced in 2016, long-term effects on GDP are still emerging. A more extensive dataset or consideration of macroeconomic shocks (such as demonetization or global downturns) would provide a clearer picture of DPI's sustained economic impact.

Government spending (% of GDP) and unemployment were included as control variables in the model to account for macroeconomic conditions that could otherwise confound the UPI-GDP relationship. While their coefficients were statistically insignificant ($p = 0.0872$ and $p = 0.1698$, respectively), their inclusion helped isolate the effect of UPI transactions by accounting for concurrent fiscal and labor-market dynamics. The negative unemployment coefficient (-673.67, $p = 0.1698$) aligns with expectations, as higher unemployment is generally associated with lower GDP. The negative coefficient for government spending (-411.15, $p = 0.0872$) is counterintuitive but not uncommon in macroeconomic models. It may reflect timing mismatches, where the economic impact of spending is delayed, or there are inefficiencies in fund allocation or the crowding-out of private investment. While we used lagged expenditure in the Aadhaar and AePS models to address this, contemporaneous spending was retained in the UPI model due to its closer link to immediate consumption.

Our analysis of Aadhaar's impact, measured through authentication volumes and AePS transactions, offers nuanced insights. Aadhaar authentication volumes showed a positive correlation with GDP growth (coefficient: 73.94, $p = 0.0263$). Additionally, unemployment (-1504.96, $p = 0.0300$) emerged as a statistically significant factor, aligning with expectations. A strong t-stat (>2 for all variables) and confidence intervals that do not include zero, further support the hypothesis that increased Aadhaar authentications are linked to higher GDP growth. Notably, our previous UPI model also showed strong t-statistics and confidence intervals excluding zero, which supports the consistency of the results across models. However, despite a high R^2 (0.9847) and adjusted R^2 (0.9732), the model's robustness warrants caution due to several limitations. First, the small sample size (eight years of data) may reduce statistical power, increasing the risk of overfitting or failing to detect weaker relationships. Second, while Aadhaar authentication volume serves as a proxy for financial inclusion, GDP is a broader value metric, potentially limiting the model's ability to capture Aadhaar's immediate impact on growth. Third, Aadhaar's economic influence unfolds gradually, driving credit access, banking adoption, and digital transactions over time. While we included lagged government spending (% of GDP) to account for these effects, its high negative coefficient (-1195.26, $p = 0.0827$) was counterintuitive, possibly indicating timing mismatches or unaccounted external factors. While our model provides preliminary evidence of Aadhaar's role in GDP growth, its statistical limitations and the multifaceted nature of Aadhaar's economic impact (spanning multiple years rather than a simple linear year-on-year effect) necessitate a more nuanced approach. To address these limitations and derive a more direct metric for Aadhaar's GDP impact, akin to UPI, we introduced AePS as a key variable. We selected AePS as a proxy for Aadhaar's direct economic influence because it reflects actual financial transactions, unlike broader Aadhaar metrics, which often serve enabling or background functions. Initial regressions using AePS transaction value, similar to UPI, yielded an unexpectedly high coefficient, exceeding that of UPI—an outcome that was statistically inconsistent and economically implausible given AePS's smaller scale and its role as a subset of Aadhaar. This inflation was likely driven by omitted variable bias, as AePS expansion often coincides with rural development efforts or welfare spending, which are difficult to isolate in a small dataset. Another possible explanation is endogeneity, whereby higher GDP levels may drive increased AePS usage rather than the reverse. In contrast, AePS volume, which reflects usage frequency rather than monetary flow, yielded a more statistically sound and economically meaningful measure. Thus, AePS volume was incorporated into the final model. Pradhan Mantri Jan Dhan Yojana accounts were also examined as a key variable in the Aadhaar-GDP regression, given their association with DPI success. However, statistical strength was lacking in the model. A deeper investigation, informed by the World Bank's Global Findex Database, indicated that while account ownership surged between 2014 and 2017, a significant proportion of accounts remained inactive, limiting their relevance for our analysis (33).

The selected model confirmed our statistical interpretations and intuitive expectations, demonstrating a clearer linkage to GDP (coefficient: 45.71, $p = 0.0201$). However, AePS represented only a subset of Aadhaar's broader influence, capturing transaction-based financial inclusion but not its full contribution to credit access, subsidy distribution, and formal banking integration. Future studies should explore alternative metrics, such as Aadhaar-linked bank account adoption, credit disbursal through Aadhaar-linked KYC (banking identity verification), and the long-term economic mobility of Aadhaar beneficiaries, to gain a more comprehensive understanding of its macroeconomic effects.

Our key finding from the regression analysis is that UPI contributed approximately 3.4% to total GDP over the study period, while Aadhaar's impact ranged between 2.53% and 4.3% annually across the two models. Using 2023–24 figures, a 10% increase in UPI transaction value corresponded to a 1.51% rise in GDP, while Aadhaar-linked financial activities drive an estimated 2.29% increase. While the small sample size (2016–2024) and the straightforward nature of our regression analysis necessitate caution in interpreting absolute estimates, the model's directional validity aligns with broader research on DPI and economic growth. BIS, the Bank for International Settlements, estimates that a 1% point increase in digital payments raises GDP per capita growth by 0.10% points over two years, while GSMA, the global mobile industry association, finds that a 10% point rise in mobile money adoption boosts GDP by 0.4% to 1.0% annually (24,25). Similarly, NASSCOM attributes 0.9% of India's GDP to digital public entities like Aadhaar and UPI, and McKinsey projects that full digital ID coverage in select economies could unlock economic value equivalent to 3%–13% of GDP by 2030 (4,12). These findings highlight digital payment systems and identity frameworks as key drivers of economic expansion, emphasizing the need for continued adoption, policy support, and integration of high-value use cases. Future research should explore long-term structural benefits, including financial inclusion, credit expansion, and productivity gains, to deepen the understanding of their macroeconomic impact.

Although statistically significant correlations were identified in all three models, causality was not inferred due

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to the observational nature of the data, the limited sample size, and potential endogeneity. Future research could strengthen causal inference by employing quasi-experimental designs such as difference-in-differences (DiD) or panel data regressions. These approaches are particularly suitable in contexts where randomized controlled trials are impractical, such as nationwide digital infrastructure rollouts like Aadhaar and UPI. DiD models, for instance, could compare economic outcomes across regions or time periods with varying exposure to DPI implementation, thereby helping to isolate net effects from broader macroeconomic trends. Panel data models, which track multiple regions over time, would allow control for unobserved heterogeneity and improve the robustness of estimates. As more granular district and state-level data become available through government portals and open-data platforms, these methods will be especially useful in disentangling overlapping effects, accounting for staggered rollouts, and providing clearer insights into how DPI influences macroeconomic outcomes such as GDP growth, financial inclusion, and subsidy efficiency.

Our UPI transaction cost analysis highlights its substantial efficiency gains over traditional payment methods. At just ₹0.0025 per ₹1 transacted, UPI significantly undercuts cash withdrawals (₹20–₹25 per transaction) and card fees (1.5%–2.5%), generating cumulative savings that grew from ₹3.56 million in FY 2016–17 to ₹5.87 trillion in FY 2023–24. While our regression independently estimated UPI's broader GDP contribution, from ₹0.30 trillion in 2017–18 to ₹17.74 trillion in 2023–24, these transaction-level savings reinforce its economic relevance. However, the distribution of these benefits is not uniform. While UPI reduces systemic friction, much of the cost advantage may be captured by intermediaries, such as banks, fintechs, and payment providers, rather than directly benefiting consumers. For instance, the government recently implemented a zero Merchant Discount Rate (MDR) policy for low-value UPI transactions benefiting small merchants (26).

Adoption patterns also remain uneven. Although UPI transactions in rural and semi-urban retail stores grew 118% in 2023, usage remains concentrated in urban and Tier-1 regions (27). Gaps in infrastructure, smartphone access, and digital literacy limit reach in rural areas, where cash still dominates low-value transactions. As such, assumptions of uniform adoption may overstate UPI's short-term macroeconomic impact. Future research should incorporate regional usage patterns and examine how cost savings are distributed across users and providers. Expanding digital access in underpenetrated areas could unlock further growth and broaden UPI's long-run contribution to GDP.

Aadhaar has significantly optimized DBT, reducing leakages and eliminating ghost beneficiaries. Transfers grew from ₹0.31T in FY 2016–17 to ₹3.34T in FY 2023–24, with savings from reduced leakages ranging between ₹0.078T and ₹0.72T. However, the decline in savings rates, from 25% in the early years to 19.35% in FY 2022–23, followed by a modest rebound to 21.43%, suggests that efficiency gains are plateauing. This is likely because most duplicate beneficiaries have already been eliminated, leaving limited scope for further savings in a system that is now largely optimized. To sustain or enhance fiscal efficiency, future gains may need to come from alternative complementary measures such as real-time benefit tracking, dynamic eligibility verification, automated grievance redressal, and stronger coordination across central and state databases to reduce exclusion and fraud. Unlike UPI, which directly impacts GDP through transaction cost efficiencies, Aadhaar's primary effect is on fiscal management. While DBT savings may indirectly boost economic growth by increasing disposable income and optimizing subsidy distribution, their core contribution lies in improving governance efficiency rather than directly expanding GDP.

In conclusion, our findings highlight the transformative role of DPI, with UPI driving cost efficiencies that support GDP growth and Aadhaar enhancing financial inclusion through more efficient welfare distribution. While these are the most direct benefits, both systems also contribute to broader socio-economic improvements, such as better governance, increased transparency, and expanded access to services, alongside gradual behavioral and structural changes. Future research should expand datasets, refine economic models, and incorporate qualitative factors like financial literacy and regional adoption patterns to gain a deeper understanding of DPI's long-term economic impact.

MATERIALS AND METHODS

Data Collection and Validation

Given the relatively recent implementation of DPI and its measurable impact during the COVID-19 pandemic, the limitations of the short review cycle were carefully considered. Government and institutional sources were primarily relied upon, and figures were cross verified across multiple official datasets to reduce the risk of reporting bias. Although independent validation of the NPCI data is not available, it remains the industry benchmark, as NPCI is the designated clearing authority for India's digital payments ecosystem, and its figures were consistent across the Press Information Bureau (PIB) of the Ministry of Finance (MoF), and NPCI sources. For instance, UPI transaction data was available from three different sources—the PIB of MoF, the NPCI website, and the NPCI retail statistics file (10, 28, 29). Cross-referencing confirmed that these figures were identical across sources, reinforcing data reliability. Similarly, GDP values and AePS transaction volumes were accessible from private platforms like Statista, but their figures for AePS transactions were nearly half of those reported in NPCI's retail statistics (30, 29). Since Statista did not disclose its data methodology, NPCI figures were selected to maintain internal consistency, as both UPI and AePS data originated from the same source. While government-reported figures may be subject to overestimation, using a singular source ensured consistency across datasets, crucial given our study's focus on directional trends rather than precise absolute estimates.

Regression Design and Variable Selection

The regression analysis was designed to be both intuitive and methodologically rigorous, and results were considered statistically significant at the 5% level ($p < 0.05$). A basic linear regression between UPI transaction value and GDP growth was initially conducted, and the model was progressively refined through the introduction of control variables to enhance statistical robustness and economic validity. Variable selection was guided by both statistical considerations and economic logic. In the UPI-GDP model, contemporaneous government spending was included as a control to reflect UPI's alignment with real-time retail activity and short-run consumption. However, Aadhaar's impact tends to be more gradual, with

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effects such as improved financial inclusion, stronger welfare targeting, and expanded banking access, becoming evident over an extended period. To reflect this delay, a four-year lag on government spending was applied in the Aadhaar model. This choice is consistent with findings from empirical macroeconomic studies and fiscal multiplier literature, which show that the effects of government expenditure often peak around 2–5 years after the initial outlay (31). Similarly, Vector Autoregression studies have demonstrated that fiscal policy shocks frequently have their maximum GDP impact at a 4–5 year lag (32). For AePS, a more transaction-based service linked to Aadhaar, a two-year lag was applied to capture its relatively quicker impact on GDP through direct withdrawals and fund transfers.

Model Diagnostics and Validation Tests

To assess model validity, heteroskedasticity tests, residual scatter plots, the DW test, and ACF test were conducted in Microsoft Excel (Microsoft 365) using regression and residual analysis outputs from the Data Analysis ToolPak. Heteroskedasticity tests showed no issues across all models, though residual plots indicated mild heteroskedasticity in the Aadhaar regression. The DW test was inconclusive due to limited data, while visual inspection of residual plots did not indicate strong correlation. ACF test results were limited in power due to the small sample size but indicated no major concerns for UPI and negative autocorrelation for Aadhaar.

Cost Analysis

For the UPI transaction cost analysis, cost estimates for debit and UPI transactions were obtained from the RBI's discussion paper on charges in payment systems (19). For credit transactions, industry and bank sources were relied upon. Cash transaction volume was proxied by cash withdrawals reported by the RBI, in alignment with other transaction volume data from the same source (20). As these data are reported monthly, they were aggregated to obtain annual figures for the review period. To estimate the average transaction cost for cash, RBI's security printing costs alongside withdrawal fees were incorporated (21). Cost savings were then estimated by comparing UPI's average transaction cost with those of other payment methods, using derived cost estimates and transaction volumes.

DBT Analysis

For the DBT savings estimates, data were obtained from the Indian government's official DBT Bharat website (22). As the figures were reported cumulatively up to March 2022, proportional allocations were made based on annual DBT transfers, using data released by the MoF (23). Notably, NASSCOM estimated DBT savings from leakage prevention at ₹0.2 trillion in 2022, whereas the government reported ₹0.64 trillion for 2022–23—a threefold difference. Since NASSCOM did not specify its methodology, and government figures may be overstated, the actual savings likely lie between these estimates (12).

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