International Journal of Emerging Research in Engineering and Technology
Pearl Blue Research Group | Volume 7 Issue 2 PP 100-118, 2026
ISSN: 3050-922X | https://doi.org/10.63282/3050-922X.IJERET-V7I2P114

Original Article

Leveraging Predictive Financial Modeling and Comparative Research for Economic Forecasting: Insights from India's Payment Systems

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Received On: 10/03/2026 ***Revised On: 09/04/2026*** ***Accepted On: 17/04/2026*** ***Published On: 23/04/2026***

Abstract *- This paper examines the transformative role of India's Unified Payments Interface (UPI) in driving the shift toward a cashless economy, with particular emphasis on its implications for financial market forecasting and investment strategies. Using the original Continuous Exponential Mohammad Asad (CEMA) model, the study analyses transaction patterns within the UPI ecosystem, revealing that its annual aggregated transaction value could surpass the GDP of several major economies. The paper also identifies key UPI clusters, offering novel insights into future growth. By applying advanced machine learning and predictive financial modelling, the study provides a unique approach to forecasting financial trends and market dynamics. While not focused on traditional corporate finance or portfolio management, it serves as a practical tool for market trend forecasting, risk management, and investment decision-making. The research holds significant value for the financial community, with broad implications for emerging economies and global markets. By integrating computational methods with economic analysis, this work presents a novel framework for modelling large-scale financial networks and delivers actionable insights for policymakers, regulators, and investors. Overall, the study advances the understanding of digital financial infrastructures, market forecasting, the stability and scalability of cashless economies, and provides computational economic models.*

Keywords *- Finance; Statistics, Predictive Modeling, Payment Systems, Comparative Analysis, Computational Economic Models.*

1. Introduction

Launched in 2016, the Unified Payments Interface (UPI) has transformed the Indian payment landscape by facilitating seamless mobile transactions and accelerating the shift toward a less cash-dependent economy. UPI's innovative design challenges the traditional dominance of payment systems and fund transfer mechanisms, such as real-time gross settlement (RTGS), national electronic funds transfer (NEFT), and immediate payment service (IMPS), establishing its pivotal role in India's financial infrastructure.

Empirical research on UPI and robust predictive modeling remains limited. This study offers a comprehensive empirical analysis of India's payment systems, focusing on UPI through rigorous statistical methods and advanced financial modeling. These include the novel application of the k-means clustering algorithm to offer new insights into transaction patterns and payment system performance and original predictive models for payment systems and fund transfer mechanisms. Previous studies have either focused exclusively on UPI (Pal *et al.* 2021, Rastogi *et al.* 2021) or briefly mentioned major payment systems. For example, the World Bank (2021) report provided a comparative analysis of IMPS and UPI but lacks a detailed empirical analysis. This study analyzed the four major payment systems (RTGS, NEFT, IMPS, and UPI) within a unified framework to understand their interactions and impacts, thus bridging the gaps in comparative studies.

This study contributes to the global discourse on digital finance by providing insights relevant to both India and other emerging economies. Its methodologies and findings can be adapted to optimize digital payment systems worldwide. It also provides actionable insights into policy decisions to improve financial systems.

2. Related Literature

UPI has been the subject of extensive debate. Many studies have questioned the sustainability of mobile payments driven by UPI during its early adoption phase. Pal *et al.* (2021, p. 1) concluded, 'To contribute significantly to financial inclusion, mobile payment usage needs to be sustained even beyond the transient forces of the initial demonetization push.' This study empirically demonstrates that UPI has not only sustained but also significantly enhanced its role as an essential pillar within India's financial ecosystem.

Few studies have suggested that mobile payments will attract a substantial user base internationally and demonstrate tremendous growth. Hoofnagle *et al.* (2012) concluded that 'mobile payment methods are suitable for offline micropayments as well as online purchases.

Some studies have highlighted the insufficient empirical research on the impact of UPI across different demographics. For instance, Rastogi *et al.* (2021, p. 519) observed, 'None of the studies empirically talks about the impact of UPI on the economic development of the poor people.

Payment methods have evolved from cash to checks, credit and debit cards, e-commerce, and mobile banking. Online payment methods are widely used for daily and on-site purchases (Khan *et al.* 2017). While earlier studies focused on individual payment systems, this study integrates RTGS, NEFT, IMPS, and UPI into a unified framework, offering a thorough comparative analysis missing from the literature on Indian payment systems.

Thus, the literature reveals significant gaps in empirical research, comparative analyses, important milestones, and new insights related to Indian payment systems. This study aims to address these gaps.

The following essential concepts were considered in this study:

- NPCI: National Payments Corporation of India
- RBI: Reserve Bank of India
- RTGS: It is a payment system with a continuous, real-time settlement of individual fund transfers on a transaction-by-transaction basis (without netting). 'Real-time' means that instructions are processed as they are received, while 'gross settlement' implies the individual settlement of funds transfer instructions (RBI 2022a). The RTGS system is primarily used for large-value transactions, with a minimum INR of 2,00,000 (approximately USD 2,424), and no upper ceiling.
- NEFT: It is a centralized payment system operated by the RBI where transactions received up to a specific cut-off time are processed in batches (RBI 2022b).
- IMPS: NEFT and RTGS were available to users for fund transfers only during banking hours. Launched in 2010, the IMPS provides an immediate, robust, and real-time fund transfer service that can be accessed through multiple channels such as mobiles, ATMs, branches, and SMS (NPCI n.d.). The maximum transfer limit through the IMPS is INR 2,00,000 (approximately USD 2,424).
- UPI: UPI is a popular mobile-first fund transfer system that allows users to make quick and convenient payments. Users scan QR codes to pay for daily goods and services. UPI is a homegrown payment system developed by the NPCI that facilitates real-time person-to-person (P2P) fund transfers with immediate credit confirmation (Fahad and Shahid 2022).
- Business decline (BD): BD refers to declined transactions due to customer-related errors, such as entering an invalid PIN or any decline not due to technical reasons related to banks or the NPCI (2024a).
- Technical decline (TD): TD refers to declined transactions for technical reasons, such as system unavailability or network issues at the bank or NPCI level.
- CIT: Customer-initiated transactions encompass scenarios in which a user initiates a transaction through UPI.
- On-us (or ONUS): Implemented from January 2021 onward, 'On-us transactions' refers to transactions that are not processed and settled through the UPI central system and appear under the 'On-us transactions' column (NPCI 2024b).

Accordingly, this study addresses the following research questions: 1) How can the growth trajectories of the RTGS, NEFT, IMPS, and UPI be compared, and how can UPI's impact be empirically analyzed?; 2) How does UPI's evolution compare to traditional payment systems and existing trends, and is the growth of digital payments led by UPI sustainable?; 3) What are the key milestones in the development of Indian payment systems?; 4) Can predictive models with an accuracy greater than 80% be developed for payment systems, and can this study present novel and precise models with the highest reported accuracy?; 5) What forecasts can be derived from these predictive models, and what are their broader economic implications?; 6) What direct, indirect, and new investment opportunities arise from the growth of digital payments?

3. Data and Methodology

This study used cross-sectional and time series data. The panel data included various aspects of the RTGS, NEFT, IMPS, and UPI from their inception in 2016 until the beginning of 2024.

Terms used in this study:

- B2B*:* Business-to-business transactions
- B2C*:* Business-to-customer transactions
- NBFC*:* Non-banking financial company

The data were collected from RBI-disclosed transaction statistics updated periodically, usually monthly (RBI 2024); and product statistics for UPI and IMPS, made public monthly by the NPCI (2024c, 2024d).

3.1. Materials and methods

The data file was in CSV format, while Python was used for data pre-processing, exploratory data analysis, and modeling. The dataset contained 2,026 entries with 26 variables (see Figure 1). The first 14 variables (Figure 1 A, index 0−13) were specific to UPI. They represented a breakdown of each app that processes UPI transactions and the monthly figures for each app in the UPI ecosystem. For these variables, the data file starts with time points 201604, April 2016, and ends with time points 2023-01, January 2023.

A. All Variables in the Dataset

```
[12]: data_with_breakdowns = pd.read_csv("indian_payments_stats_by_mohammad_asad.csv", encoding="ISO-88
      data_with_breakdowns.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2026 entries, 0 to 2025
Data columns (total 26 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   YEAR            2021 non-null   float64
 1   MONTH           2022 non-null   object
 2   Sr.No.          2021 non-null   float64
 3   APP             2021 non-null   object
 4   CIT_Volume      1559 non-null   object
 5   CIT_Value       1559 non-null   object
 6   B2C_Volume      1559 non-null   object
 7   B2C_Value       1559 non-null   object
 8   B2B_Volume      1502 non-null   object
 9   B2B_Value       1502 non-null   object
 10  ONUS_Volume     1502 non-null   object
 11  ONUS_Value      1502 non-null   object
 12  TOTAL_Volume    2021 non-null   object
 13  TOTAL_Value     2021 non-null   object
 14  upi_year        95 non-null     object
 15  upi_bank        95 non-null     float64
 16  upi_volume      95 non-null     object
 17  upi_value       95 non-null     object
 18  imps_year       95 non-null     object
 19  imps_bank       95 non-null     float64
 20  imps_volume     95 non-null     float64
 21  imps_value      95 non-null     object
 22  neft_lakh       95 non-null     float64
 23  neft_amount_cr  95 non-null     object
 24  rtgs_lakh       95 non-null     float64
 25  rtgs_amount_cr  95 non-null     float64
dtypes: float64(8), object(18)
memory usage: 411.7+ KB
```

B. Heat Map of All Variables in the Dataset

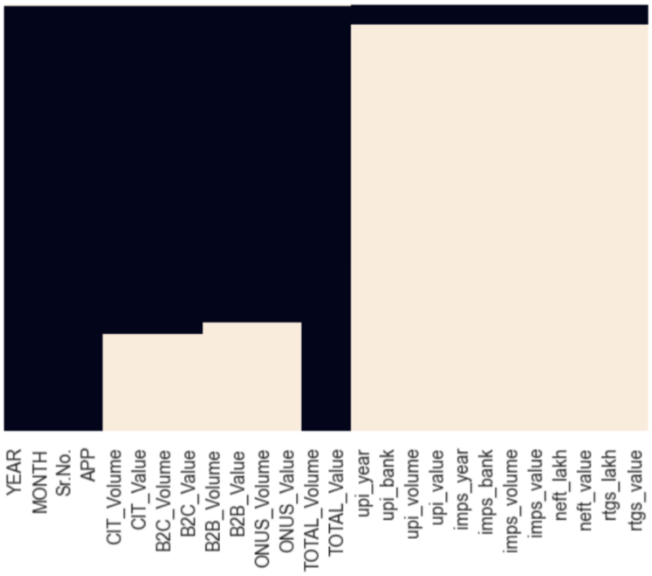

Fig 1: Information on All the Variables in the Dataset

The following 12 columns, indexes 14–25, contain only 95 entries, as seen in Figure 1B, corresponding to four major payment systems and fund transfer mechanisms in India: RTGS, NEFT, IMPS, and UPI.

Null entries or entries without added values were examined for data preprocessing. The heat map (Figure 1B) highlights the concentration of missing entries for the variables. The missing values for CIT, B2C, B2B, and ONUS were either irrelevant to those apps or not broken down by those apps, and they provided the total. Their net effects were captured in the 'total_volume' and 'total_value' features. Consequently, the CIT, B2B, B2C, and ONUS variables were insignificant and not analyzed.

Entries with a dash ('-') were also found, signifying no data for them. In addition, I presented all volumes in millions and all values in crores, where one crore = 10 million. Although the heat map in Figure 1B shows nearly 96% missing values for the last 12 variables, these entries (not missing) span 95 months (April 2016 to February 2024) and 95 corresponding entries. These variables, representing total monthly numbers for each payment system, are addressed separately in Figure 2.

A. Last 12 Variables in the dataset

```
[28]: data=data_with_breakdowns.loc[0:94,['upi_year','upi_bank','upi_volume','upi_value','imps_year','imps_bank','imps_volume','imps_value','neft_l
      data
```

[28]:	upi_year	upi_bank	upi_volume	upi_value	imps_year	imps_bank	imps_volume	imps_value	neft_lakh	neft_value	rtgs_lakh	rtgs_value

95 rows × 12 columns

B. Descriptive stats of these Variables

[9]:

	upi_bank	imps_bank	imps_volume	neft_lakh	rtgs_lakh	rtgs_value
count	95.000000	95.000000	95.000000	95.000000	9.500000e+01	9.500000e+01
mean	203.663158	510.694737	261.719474	2895.942117	1.441784e+07	1.071145e+07
std	147.208031	198.855345	166.207227	1488.033291	4.794004e+06	2.208051e+06
min	21.000000	143.000000	26.780000	1118.400000	5.434644e+06	6.443653e+06
25%	94.000000	352.500000	109.855000	1744.400000	1.085911e+07	8.953639e+06
50%	148.000000	573.000000	228.080000	2401.000000	1.274210e+07	1.057209e+07
75%	309.000000	647.000000	445.400000	3750.500000	1.897996e+07	1.231467e+07
max	560.000000	856.000000	534.630000	6889.230000	2.480131e+07	1.612290e+07

Fig 2: Last 12 Variables in the Dataset and Their Descriptive Statistics

Next, thousands of separators from all the numeric values were removed, null entries were replaced with ‘0,’ and object-type values were converted to numeric float values. This explains why Figure 2B has six features instead of the 12. The remaining 12 variables, which are significant in this study, can be described as follows:

- *upi_year:* year and month of statistics for all RTGS, NEFT, IMPS, and UPI.
- *upi_bank*: total number of financial institutions, including banks, NBFCs, and other apps active in the UPI ecosystem.
- *upi_volume*: total number of financial transactions conducted on the UPI platform.
- *imps_bank*: number of banks active in processing IMPS transactions.
- *imps_volume*: total number of financial transactions using IMPS.
- *imps_value*, *neft_value*, *upi_value*, *rtgs_value*: total value of all the transactions on respective IMPS, NEFT, UPI, and RTGS platforms. All transactions are in crores, meaning 10 million INR.
- *neft_lakh*, *rtgs_lakh*: total financial transactions on NEFT and RTGS, respectively, in lakhs (1 lakh = 0.1 million). All volumes are in millions, except where explicitly specified. This value must be converted to millions for uniformity in the dataset.

Next, an additional feature called *V2V (value per volume)* for each payment system was engineered by dividing each month’s transaction value by its volume.

A crucial consideration for transaction value is the USD to INR exchange rate, which fluctuates between 81.5 and 83.7. For simplicity, the exchange rate was fixed at 82.5 INR per USD from 2016 to 2024 (1 USD = 82.5 INR). As the figures reported by the RBI are in the INR, this conversion becomes important for USD-related calculations.

This study applies unsupervised machine learning (ML) clustering techniques and the elbow method to determine the optimal number of clusters, ‘k.’ The method identifies ‘k’ by plotting within-cluster sum square (WCSS) values on the y-axis against the number of clusters on the x-axis. ‘A marked flattening of the graph suggests that the combined clusters are very dissimilar; thus, the appropriate number of clusters is found at the “elbow” of the graph. Alternatively, the graph may have more than one elbow, indicating that more than one natural set of clusters fits the data’ (Ketchen Jr. and Shook 1996, p. 446).

The clusters identified for the different payment systems were as follows: RTGS (3), NEFT (4), IMPS (3), and UPI (3).

Throughout this study, growth percentages were modeled using random forest (RF) regression models. I used linear regression, referred to as the ordinary least squares (OLS) model. The OLS model from the stats model library in Python was used for the same purpose. Autoregressive integrated moving average (ARIMA) models were used to model univariate time series. For the clustering technique, the k-means algorithm was used, which segments different types of users on a platform. I also developed original models called the Continuous Exponential Mohammad Asad (CEMA) models for trend modeling and forecasting.

A limitation of RF models is that they cannot predict numbers outside the range of their trained data values, necessitating frequent retraining every four to six months. One drawback of direct OLS models is that they are too simple for our data, although they help to establish an overall trend and simple relationships among variables. Conversely, ARIMA models do not establish a clear relationship and more often predict higher values for our data. Alternatively, the original CEMA models presented in this study are more *significant and useful, as they provide accurate, accurate relational equations and forecasts.*

Next, box plots were drawn to analyze potential data issues. The box plots in Figure 3 show that most aspects of payment systems are either skewed or have outliers, except for the NEFT value, RTGS value, and NEFT's V2V. Skewness and outliers in other datasets were addressed during modeling.

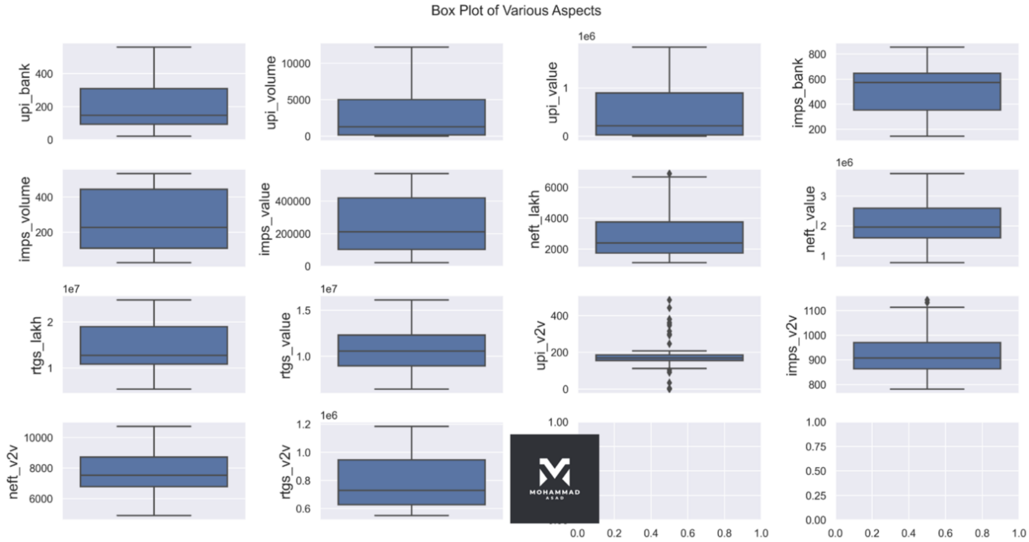

Fig 3: Box Plots of All the Features Related to RTGS, NEFT, IMPS, and UPI

Log transformation was applied to each variable to test for linearity. The results of the log transformation (Figure 4) indicate that the NEFT volumes (*neft_lakh*) appear linear. The log of NEFT's V2V from 2019 onward appears linear in Figure 4; however, it was verified using quantitative methods during modeling. Features that appear nonlinear or exponential in a graph do not require individual verification.

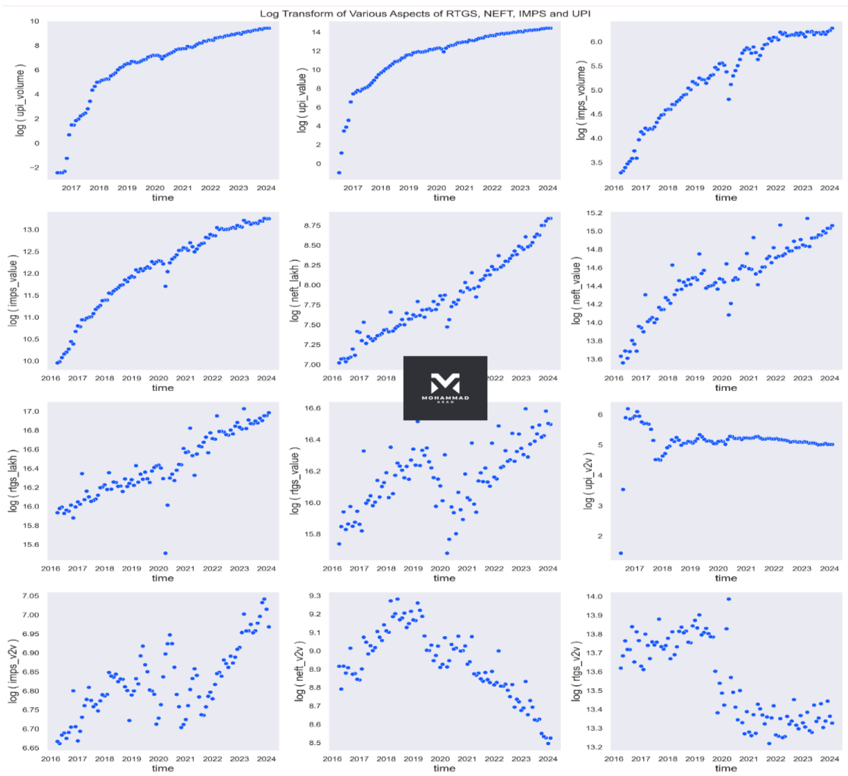

Fig 4: Logarithmic Transformed Values of All the Selected Features

4. Data Analysis and Insights

This section focuses on insights, milestones, and quantifiable historical figures for the different aspects of the payment systems in this study. As Ralph Waldo Emerson poetically stated, 'It is not the destination; it is the journey.' Below, I empirically describe the journey of these payment systems.

4.1. Period

The dataset spans April 2016, when UPI was launched, until February 2024.

4.2. Banks and financial institutions

UPI started with 21 banks in 2016, and by February 2024, 560 financial institutions were on board. Its yearly growth rate of 67.375% translates to an average of five new banking partners per month (Figure 5). Similarly, IMPS started with 143 banks and now has 856 banks processing IMPS transactions, equating to an average of seven new banking partners per month.

Interestingly, since January 2023, UPI has shown a monthly growth rate of 12.5%, translating to an average of 12 new banking partners per month, more than double its onboarding rate from 2016 to 2024.

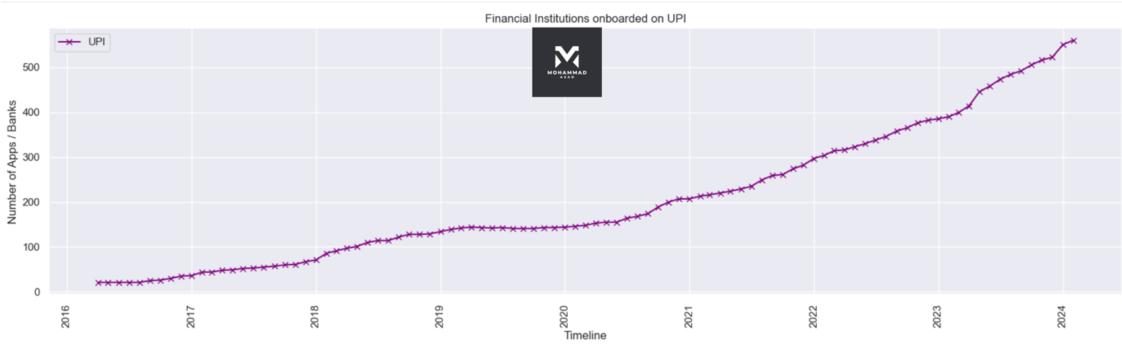

Fig 5: Number of Financial Institutions Onboarded since the Inception of UPI until February 2024

4.3. Transaction volumes

By the end of 2018, UPI surpassed all traditional payment systems and fund transfer mechanisms (RTGS, NEFT, and IMPS) in terms of transaction volume. By early 2019, UPI had established itself as the largest platform in monthly and yearly transaction volumes within three years of its launch. As of 2024, UPI is 17.7 times larger than NEFT, India's second-largest payment system. In October 2019, UPI crossed the one billion mark, and by August 2023, it had reached 10 billion transactions. Currently, UPI processes an average of 12 billion transactions per month.

Since 2021, the ranking of total yearly transaction volumes has been UPI > NEFT > IMPS > RTGS. The trends in the monthly transaction volumes of these four financial systems are shown in Figure 6, where MA3 represents the three-month moving average.

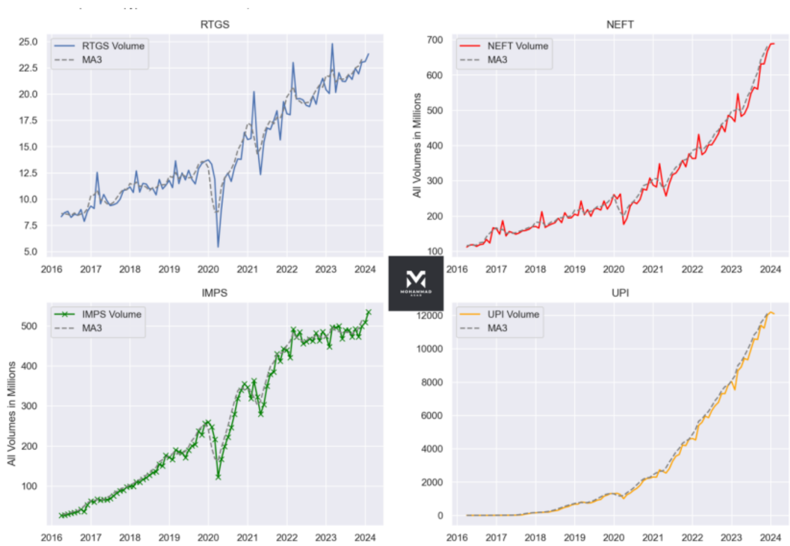

Fig 6: Trends for Monthly Volumes of Payment Systems

RTGS was the only financial payment system to see a decline in yearly transaction volume from 2016 to 2024, with a 1.2% decline in 2020. After the COVID-19 pandemic, financial payment systems continued to show positive year-on-year growth, although growth rates for UPI, IMPS, and RTGS have been declining, whereas NEFT's growth rate has continued increasing.

4.4. Transaction value

In 2020, UPI overtook IMPS in total yearly transaction value but remained behind RTGS, India's most extensive payment system, in terms of yearly transaction value. UPI is unlikely to surpass RTGS in terms of the value of yearly transactions in the foreseeable future because of the very nature of its design. As of March 2024, UPI has an upper limit of 0.1 million INR per day, whereas RTGS has a minimum value of INR 0.2 million (approximately USD 2,424). Figure 7 illustrates the growth in UPI's monthly transaction value. By 2024, RTGS will be approximately 4.5 times larger than NEFT in terms of transaction value, followed by UPI and IMPS.

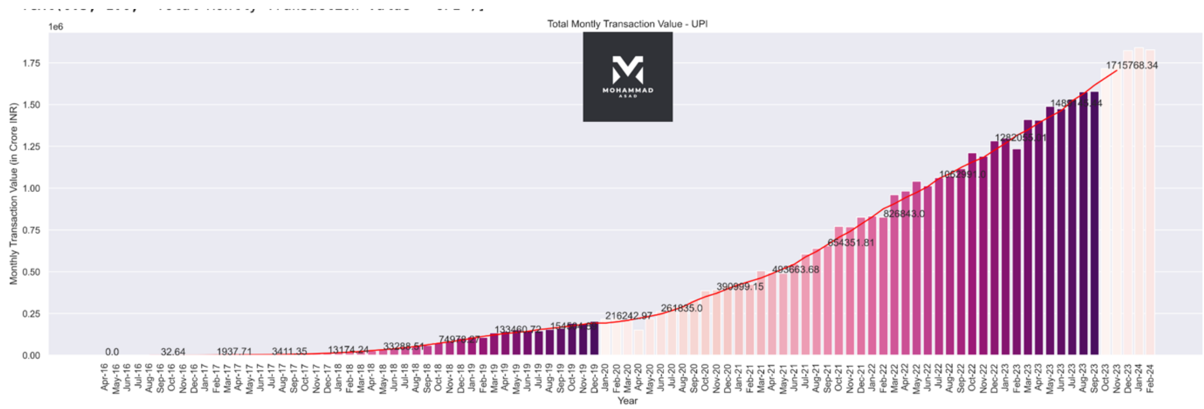

Fig 7: Monthly Transaction Values of UPI Since 2016

4.4.1. Some Insights on UPI Transaction Value

- Crossed 1 billion USD monthly transaction value in November 2017
- Crossed 10 billion USD monthly transaction value in November 2018
- Crossed 100 billion USD monthly transaction value in December 2021
- Crossed 200 billion USD monthly transaction value in October 2023

4.4.2. Some Insights on IMPS Transaction Value

- Crossed 10 billion USD monthly transactions value in December 2017
- Crossed 50 billion USD monthly transactions value in March 2022

4.4.3. Some Insights on NEFT Transaction Value

- Crossed 300 billion USD monthly transactions value in March 2019
- Crossed 400 billion USD monthly transactions value in March 2022

4.4.4. Some Insights on RTGS Transaction Value

- Crossed 1.5 trillion USD monthly transactions value in March 2018
- Crossed 2 trillion USD monthly transactions value in March 2024

From 2016 to 2024, the RTGS was the only payment system to experience a decline in total yearly transaction value, with a 24.2% decline in 2020. All other payment systems showed positive year-on-year growth, with UPI exhibiting the highest growth rate (see Figure 8). RTGS is not included in Figure 8 because of its significantly higher transaction value. Notably, in Figure 8, the graph declined because only two months were recorded for 2024. Nonetheless, the monthly values were much higher than they were previously.

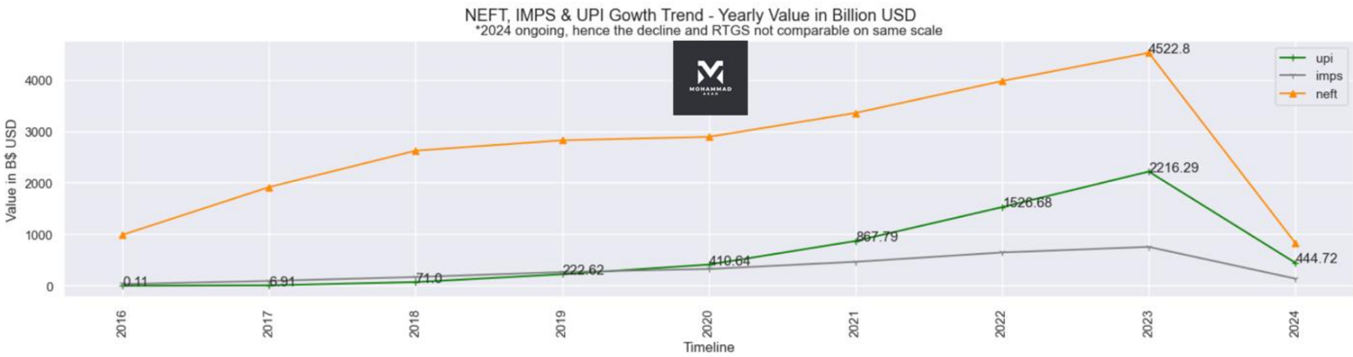

Fig 8: Growth in Yearly Transaction Values for NEFT, IMPS, and UPI

Examining monthly transaction values, all public financial systems saw a substantial decline in 2020 during the COVID-19 pandemic. In April 2020, RTGS declined by 46.5% from the previous month's total value, NEFT by 42.8%, IMPS by 40%, and UPI by 26.8%. Figure 9 shows the changes in the monthly values across these payment systems.

Fig 9: Trends for Percentage Change in Transactions Each Month

4.5. Value per million (V2V)

The value of transactions per million transactions (V2V) reveals interesting insights. V2V for RTGS > NEFT > IMPS > UPI is defined by the inherent design of these payment systems. Figure 10 shows that RTGS's V2V of RTGS has been declining, NEFT's V2V has been declining since 2019, and IMPS's V2V has been increasing. UPI V2V rallied in 2016 and 2017, declined in 2017 and 2018, and has since remained within a narrow range, rising from 2018 to 2021 and declining from 2021 to 2024.

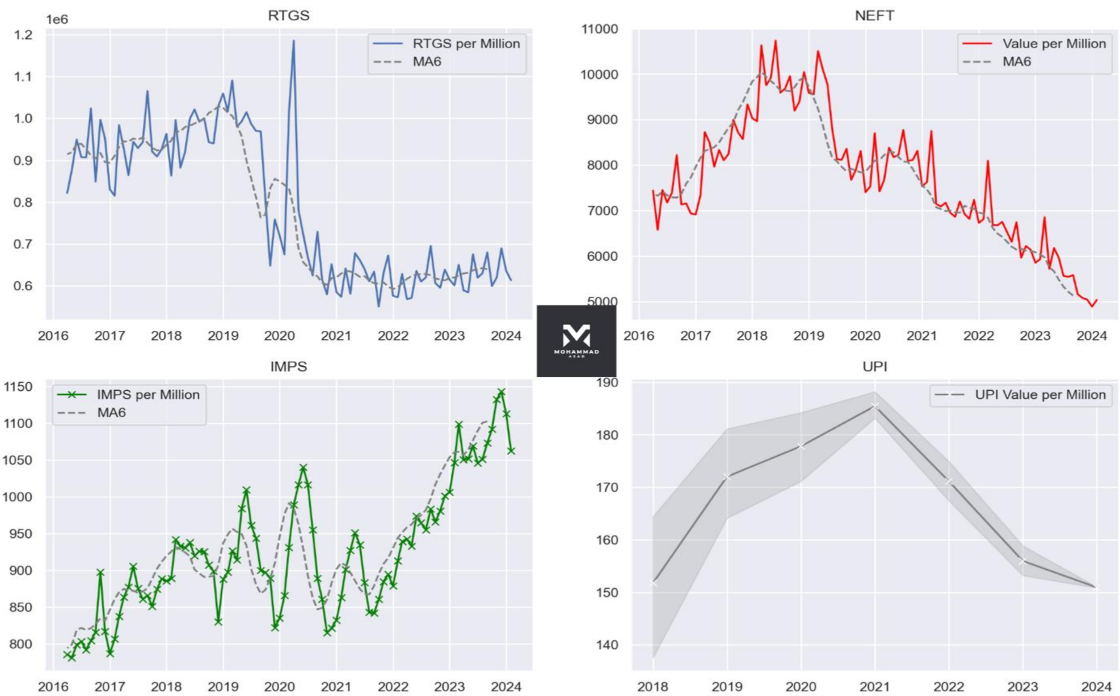

Fig 10: The Journey of V2V or Transaction Value Per Million

5. Data Modeling and Original Models

While the previous section primarily dealt with historical numbers, this section reviews predictive modeling for forecasting and understanding present trends, using the unsupervised ML clustering technique.

5.1. Clustering

The k-means clustering technique was used on each financial system. Although it did not reveal any significant insights for RTGS, NEFT, and IMPS, it provided valuable insights for UPI.

Figure 11 shows the clustering results, where different colors and shapes represent different clusters. When UPI was in the early adoption phase, it showed two types of clusters**:** *low V2V transactions with low volumes (Cluster 1 in Figure 11) and high V2V transactions with low volumes (Cluster 3 in Figure 11).*

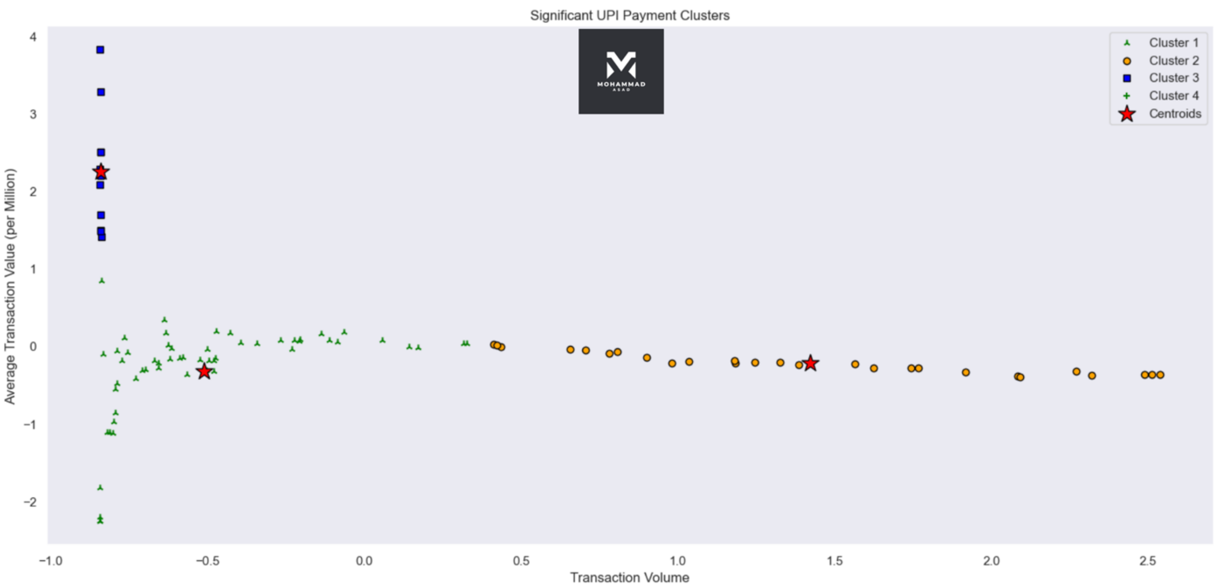

Fig 11: Customer Segmentation Clusters of UPI

As UPI adoption matured and crossed its adoption chasm curve, even though ecosystem adoption numbers in terms of value and volume of transactions and the number of banks and apps adopting it increased manifold, V2V transactions started decreasing, showing the third and final cluster of *medium V2V transactions with high volumes (Cluster 2 in Figure 11).*

This indicates UPI adoption by the masses in Cluster 2 (the current cluster). Upon deeper analysis, Cluster 3 has values for 11 months, a mean of 360 crore V2V, starting when the monthly value was 32.64 crore and ending when the volume was 11.6 million. Cluster 1 has values ranging from 0 to 247.4 crore V2V.

5.2. Value

I started by modeling the percentage change in monthly transaction values or growth percentages, which is equivalent to modeling volatility without a trend component. Similar to the earlier growth rate, Figure 9 shows that the NEFT and RTGS experienced considerable growth spikes in March and negative growth spikes in April. The COVID-19 pandemic in 2020 was a rare event, resulting in only one year with additional spikes, and can thus be treated as an outlier.

The data were divided into training and test sets in a 70:30 ratio. Table 1 summarizes the results of the RF and linear regressions.

Table 1: Regression Fit Results on Transaction Value Growth %

	Training data		
	RF	Linear regression	RF on test data
RTGS	88.90%	Not suitable	
R-squared (R2)	0.889	0.0064	0.8140
NEFT	91.43%	Not suitable	
R-squared (R2)	0.9143	-0.064	0.7401
IMPS	86.97%	Not suitable	
R-squared (R2)	0.8697	-0.301	0.3110
UPI	83.74%	Not suitable	
R-squared (R2)	0.8374	0.077	0.3985
RF: random forest regression model RTGS: real-time gross settlement NEFT: national electronic funds transfer IMPS: immediate payment service UPI: Unified Payments Interface.			

Table 1 presents that linear regression results are not significant (below 7%) and sometimes negative, making it unsuitable for modeling transaction values. RF algorithm yields results greater than 83% for all four systems, but test data R-squared values decline. RTGS outperforms with 0.8140 R-squared.

While actual numbers largely vary, this model captures the overall trend. Forecasted growth percentages from March to July 2024 for all four systems are presented in Table 2, with goodness of curve fit accuracy shown in Figure 12.

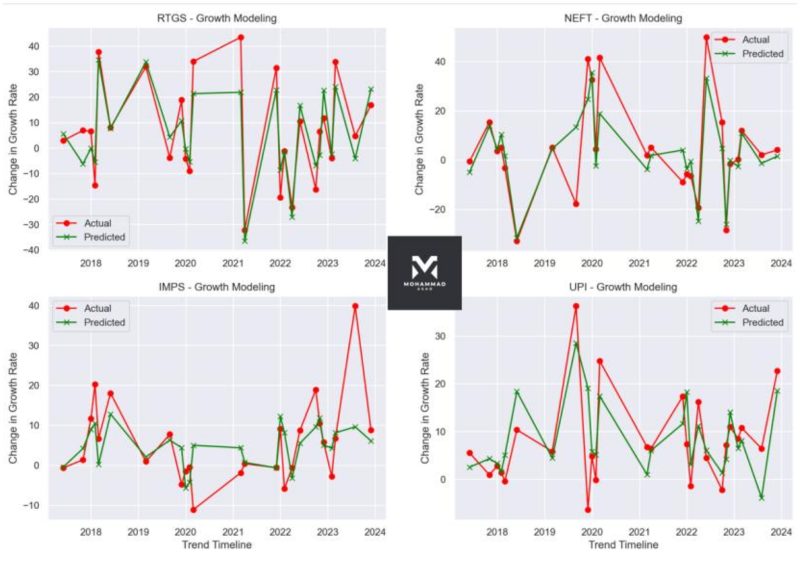

Fig 12: Forecast of Transaction Value Growth by the Random Forest Regression Model against Actual Data to Visualize the Goodness of Fit

Table 2: Predicted Change in Transaction Values for 2024 (March to July) for Random Forest (RF) Models

Year	Month	RTGS %	NEFT %	IMPS %	UPI %
2024	3	23.99	25.03	11.36	8.89
2024	4	-28.77	-24.73	-5.56	-1.21
2024	5	6.46	2.02	2.12	4.54
2024	6	12.97	2.7	4.4	0.36
2024	7	-5.18	0.92	1.61	3.04
RTGS: real-time gross settlement; NEFT: national electronic funds transfer; IMPS: immediate payment service; UPI: Unified Payments Interface					

Table 3: Random Forest (RF) Regression Results on Volume Growth (%)

	R^2 on training data	R^2 on test data
RTGS	0.8957	0.44807
NEFT	0.90522	0.6275
IMPS	0.82380	0.28549
UPI	0.821047	0.089054
R^2: R squared test results; RTGS: real-time gross settlement; NEFT: national electronic funds transfer; IMPS: immediate payment service; UPI: Unified Payments Interface.		

5.3. Volumes

Transaction volumes were modeled using different ways to obtain the best results. Volume growth changes were modeled using an RF regressor, OLS was used for modeling actual volumes, and ARIMA was used for modeling the univariate time series. Table 3 presents the results for the RF model. A higher R-squared (R^2) value indicates a better fit and the ability to explain variable variability.

Table 4 lists the forecast values for future months using these models and the volumes derived from these percentages. The curve fit accuracy for these models in Figure 13 compares the RF model's fitted transaction volumes with actual transaction volumes, with green indicating future forecast percentages.

Table 4: Predicted Growth Percentages and Volumes for 2024 (March to August), RF Models

	UPI%	IMPS%	NEFT%	RTGS%	UPI from %	IMPS from %	NEFT from %	RTGS from %
Mar	10.6432	8.5772	15.585	17.01	13390.79	580.4863	796.291	27.8779
Apr	-0.0840	-4.5280	-11.265	-16.58	13379.54	554.2018	706.589	23.2560
May	6.26999	0.8833	0.75	5.53	14218.44	559.0973	711.897	24.5398
Jun	2.37507	-2.2415	4.509	2.491	14556.13	546.5649	743.998	25.1509
Jul	4.76284	2.7051	5.662	2.902	15249.42	561.3499	786.118	25.8808
Aug	5.09319	0.9453	3.781	1.761	16026.11	566.6564	815.838	26.3364

RTGS%: real-time gross settlement growth percentage forecast;
NEFT%: national electronic funds transfer growth percentage forecast;
IMPS%: immediate payment service growth percentage forecast;
UPI%: Unified Payments Interface growth percentage forecast.

UPI from %: Actual UPI volume corresponding to the forecast percentage;
IMPS from %: Actual IMPS volume corresponding to the forecast percentage;
NEFT from %: Actual NEFT volume corresponding to the forecast percentage;
RTGS from %: Actual RTGS volume corresponding to the forecast percentage.

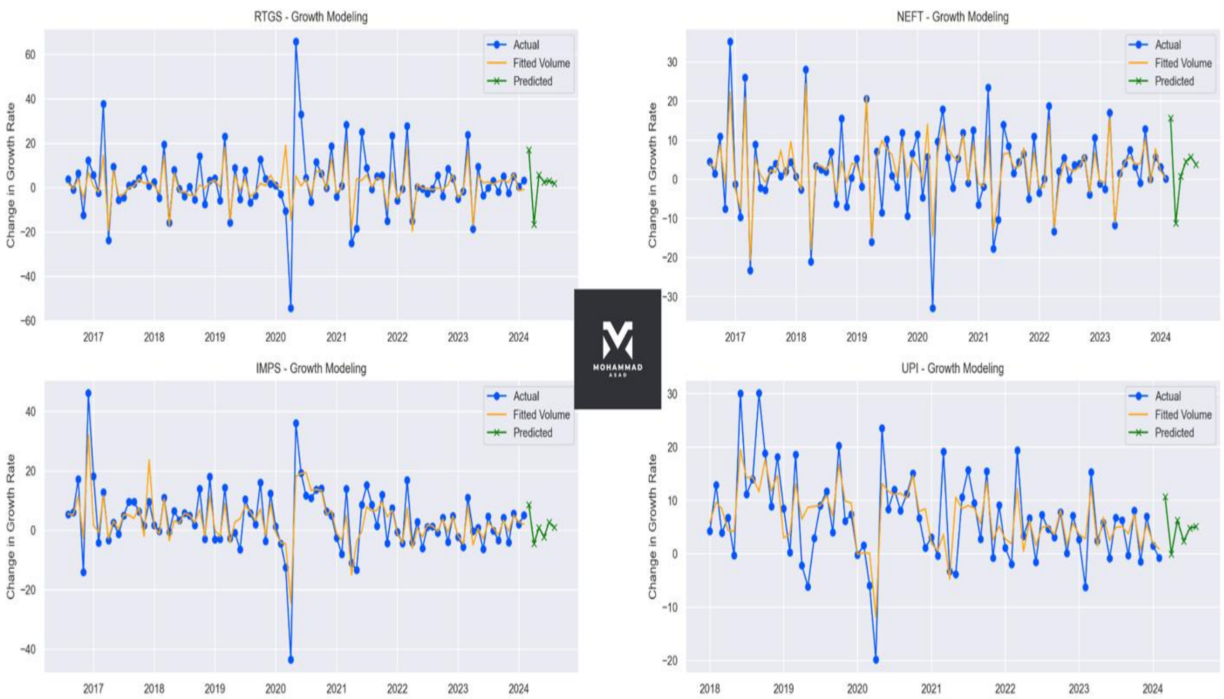

Fig 13. Model Fit or Projected Monthly Transaction Volume Growth against Actual Transaction Volume Growth Percentage

Next, OLS models were computed along with their error percentages. A model with an average error (ϵ) percentage of 8.8% falls under the 90% confidence level, while a model with a 4% error falls under the 95% confidence level. A model below 1.9% (ϵ) signifies a 98% confidence level. Only models with error percentages within acceptable ranges were retained.

P>|T| in Table 5 describes the *p*-values of the various coefficients. In Table 5, *NEFT_OLS* and *NEFT2021_OLS* are different OLS models for NEFT, where *NEFT_OLS* is trained on default timeline data (2016−2024), and *NEFT2021_OLS* is trained on data from 2021 to 2024. *NEFT_OLS* since 2017 is the same as the *NEFT_OLS* model but considers monthly forecasts from 2017 onward. Although Table 5 does not explicitly mention NEFT_OLS since 2017, it is technically the same as the *NEFT_OLS* model. This nomenclature and understanding are consistent with all the other payment system models.

One key understanding from this OLS model fitting for linear regression on volumes (Table 5) is that the constant term (intercept), year, and month are significant for all payment systems as their p-values are below 0.05. IMPS achieved the best R^2 result of 95.5% among the default timeline models, while *UPI2021_OLS* yielded the best R^2 score of 0.99 across all volume models.

Table 5: OLS Results and Coefficients for Transaction Volumes of Payment Systems

	COEF	**STD ERR**	T-Stat	**P>|T|**	**[0.025**	**0.975]**	**R^2**	**F-STAT**
RTGS							0.849	258.6
CONST	-3867.99	170.812	-22.64	0	-4207.245	-3528.75		
YEAR	1.9219	0.085	22.73	0	1.754	2.09		
MONTH	0.12	0.056	2.13	0.036	0.008	0.232		
NEFT							0.861	284.8
CONST	-1.21E+05	5087.122	-23.81	0	-1.31E+05	-1.11E+05		

YEAR	60.1005	2.518	23.87	0	55.099	65.102		
MONTH	4.9888	1.68	2.97	0.004	1.652	8.325		
NEFT2021_OLS		0.92	161.4					
CONST	-2.78E+05	1.55E+04	-17.91	0	-3.09E+05	-2.46E+05		
YEAR	137.4732	7.662	17.94	0	121.779	153.168		
MONTH	12.2224	1.747	6.99	0	8.645	15.8		
IMPS							0.955	983.9
CONST	-1.43E+05	3220.432	-44.27	0	-1.49E+05	-1.36E+05		
YEAR	70.7068	1.594	44.35	0	67.541	73.873		
MONTH	6.4578	1.064	6.07	0	4.345	8.57		
UPI							0.808	194
CONST	-2.87E+06	1.46E+05	-19.67	0	-3.16E+06	-2.58E+06		
YEAR	1420.0722	72.108	19.69	0	1276.859	1563.286		
MONTH	137.5255	48.111	2.859	0.005	41.973	233.077		
UPI2021_OLS	0.99	1537						
CONST	-7.12E+06	1.28E+05	-55.39	0	-7.38E+06	-6.85E+06		
YEAR	3520.844	63.501	55.44	0	3391.333	3650.355		
MONTH	321.9717	16.038	20.07	0	289.262	354.681		
COEF: coefficients; P>|T|: p-values.								

Next, the models based on the error terms or ϵ % were investigated. Table 6 lists the total errors of the models during the training period and the average error (ϵ %) by which the forecasts are expected to vary.

Table 6: Errors (ϵ) of the OLS Models

Models on monthly value	**T(ϵ)**	**∓(ϵ)**	**Verdict**
RTGS_OLS	-66.317352	9.068	☑☐
NEFT_OLS	577.375515	19.757	Not acceptable
NEFT2021_OLS	-5.899482	5.424	☑☐
IMPS_OLS	-500.22571	16.525	Not acceptable
IMPS_OLS since 2020-09	-135.899	7.544	☑☐
UPI_OLS	6885.35893	82.415	Useless
UP2021_OLS	-19.173	3.625	☑☐
Same models on the yearly sum	T(ϵ)	%(ϵ)	Verdict
RTGS_OLS	-11.26201	7.02	☑☐
RTGS_OLS since 2021	-10.82839	3.72	☑☐
NEFT_OLS since 2017	-12.95574	14.12	Not acceptable
NEFT2021_OLS	4.59556	1.54	Excellent
IMPS_OLS since 2017	19.7007	6.95	☑☐
UPI_OLS	338.9491	51.05	Useless
UP2021_OLS	11.59731	3.87	☑☐
T(ϵ): Total sum of residual of the fitted data; ∓(ϵ): Positive or negative error percentage.			

T (ϵ) = Total sum of residuals from the fitted data of the models. It indicates that overall, the model predicts higher values than actual or lesser values if T (ϵ) is negative.

∓ (ϵ) or % (ϵ) = Error percentage by which the projected values vary on average. It also provided a range of confidence levels.

The first half of Table 6 presents error (ϵ) for OLS models, whereas the second half presents errors (ϵ) for the same models but with their values summed for corresponding years. These yearly sums are compared with the actual yearly transaction volumes.

A notable observation from Table 6 presents that *UPI_OLS* is useless, with projections varying from the actual values by more than 82%, resulting in 15% confidence in the model. *RTGS_OLS* has an above average % (ϵ) with 90% confidence in the RTGS model. Other models with 90% confidence are *NEFT2021_OLS* and *IMPS_OLS* since 2020. The best model with 95% confidence is *UPI2021_OLS*, at approximately 3.7% (ϵ); however, this model can only be used for values after 2021.

Moving to the second half of Table 6, the % (ϵ) improves compared to monthly projections. On yearly volumes, *NEFT2021_OLS* works best with 98% confidence and a very good (ϵ) of 1.6%. *RTGS_OLS* since 2021 and *UPI2021_OLS* have good % (ϵ) and 95% confidence. The worst-performing models from the acceptable models are *RTGS_OLS* and *IMPS_OLS* since 2017, with a % (ϵ) of approximately 7% each and 90% confidence.

Table 7 presents the predictions for the total yearly values of all financial systems for 2024 and 2025. The 'error (ϵ) adjusted' column is relevant only for OLS models and contains adjusted values for the maximum positive error. The 'series & model' column includes three types of information:

payment system, model name, and the hyper-parameters used. The monthly model values were summed for the corresponding year to yield the yearly values.

Table 7: Predicted Total Yearly Volumes for 2024 and 2025: OLS and ARIMA Models

	2024		2024 Error adjusted		2025	
Series & Model	Yearly	Monthly mean	$\mp(\epsilon)$	Adjusted yearly	Yearly	Monthly average
RTGS_OLS	272.01	22.67	7.02%	291.6	295.07	24.59
NEFT_OLS	6570.32	547.53	14.12%	7498	7291.52	607.63
NEFT2021_OLS	8343.84	695.32	1.54%	8473.1	9993.52	832.79
IMPS_OLS	6781.79	565.15	6.95%	7253.1	7630.27	635.86
UPI_OLS	109582.2	9131.85	51.05%	165469	126623.02	10551.92
UPI2021_OLS	160278.1	13356.51	3.87%	166480.9	202528.19	16877.35
UPI ARIMA(2,1,1)	162958.1	13579.84			202529.8	16877.48
UPI2021 ARIMA(4,0,4)	163336.9	13611.41			193469.86	16122.49
UPI2021 2nd Model ARIMA(2,1,1)	163349.6	13612.47			204944.76	17078.73
IMPS ARIMA(2,1,1)	6600.12	550.01			7395.04	616.25
NEFT ARIMA(1,1,2)	9104.64	758.72			11293.04	941.09
RTGS ARIMA(1,2,0)	310.45	25.87			379.14	31.6

$\mp(\epsilon)$: Positive or negative error percentage;
Adjusted yearly: Yearly volume after adjusting the error value corresponding to its error %.

One notable observation is that all ARIMA-predicted values are generally higher than OLS values, except for the *IMPS_OLS* model. The *UPI_OLS* model was not considered because it is useless for predictions. *NEFT_OLS* model was ignored whenever possible owing to its high error percentage (prediction marked in red).

Accordingly, a few concluding observations of these predictions are:

- For IMPS, the maximum predicted volume for 2024 is 7253.1, and the minimum volume is 6309; both are the maximum plus- and minus-error-adjusted values of the OLS model.
- For UPI, the maximum predicted volume for 2024 is 166480.9, and the minimum volume is 154075; both are the maximum error-adjusted values of the *UPI2021_OLS* model.
- For NEFT, the maximum predicted volume for 2024 is 9104.64, given by the ARIMA (1,1,2) model, and the minimum volume is 8215, which is the maximum minus the error-adjusted value of the *NEFT2021_OLS* model.
- For RTGS, the maximum predicted volume for 2024 is 310.45 million, given by the ARIMA (1,2,0) model, and the minimum volume is 252 million, which is the maximum negative error-adjusted value of the *RTGS_OLS* model.

An interesting takeaway from the ARIMA (4,0,4) model is its prediction that UPI will reach its late majority curve by 2027 and decrease in volume after peaking at 17.5 billion monthly transactions. This is one of the reasons for the development of the second ARIMA model for the *UPI2021*.

5.4. Volume equations calculated

'Year' can take any value from 2016 onward, and 'Month' can take any value from 1 to 12, inclusive, except when explicitly specified. The ∓ % is the error (ϵ) term by which our values could increase or decrease.

RTGS(Y) Volumes Equation
Y = (-3867.9974 + 1.9219* Year + 0.1200* Month) ∓ 9%
In 2016, 'Month' starts at 10 (October).

NEFT(Y) Volumes Equation
Y = (-277629.8894 + 137.4732* Year + 12.2224* Month) ∓ 5.4%
Suitable for 'Year' 2021 onward. For 2021, 'Month' starts at 7 (July).

IMPS(Y) Volumes Equation:
Y = (-142587.4722 + 70.7068* Year + 6.4578* Month) ∓ 7.5%
Suitable for 'Year' 2016 onward, but results are better from 9 (September) in 2020.

UPI(Y) Volumes Equation
Y = (-7114925.4005 + 3520.8444* Year + 321.9717* Month) ∓ 3.6%
Suitable for 'Year' 2021 onward; for 2021, 'Month' starts at 5 (May).

5.5. Value per Million (V2V)

I began by modeling V2V. For NEFT V2V, I use the OLS model. For RTGS, IMPS, and UPI, the developed CEMA model is used. These models are the original models developed in the study and are not based on existing standard algorithms or traditional techniques, such as linear regression or supervised ML.

Table 8 shows that all V2V models predict an excellent error margin and a confidence of 95% or more. The NEFT model remains valid from 2018 until 2030, around or before which the slope changes in the opposite direction, and V2V starts rising, unlike the ongoing decrease in yearly V2V. Similarly, the RTGS V2V model remains effective until 2035, when the trend eventually changes. Figure 14 compares the model forecasts against the actual numbers.

Table 8: Errors (ϵ) of the V2V Models – CEMA Models

	T(ϵ)	%(ϵ)	Verdict	
RTGS CEMA	-0.513	3.198	Good	☑☐
IMPS CEMA	11.826	1.959	Excellent	☑☐
UPI CEMA since 2017	15.042	2.512	Very good	☑☐
NEFT OLS (2018 to 2030)	-0.045	0.687	Excellent	☑☐
CEMA: Continuous exponential Mohammad Asad models.				

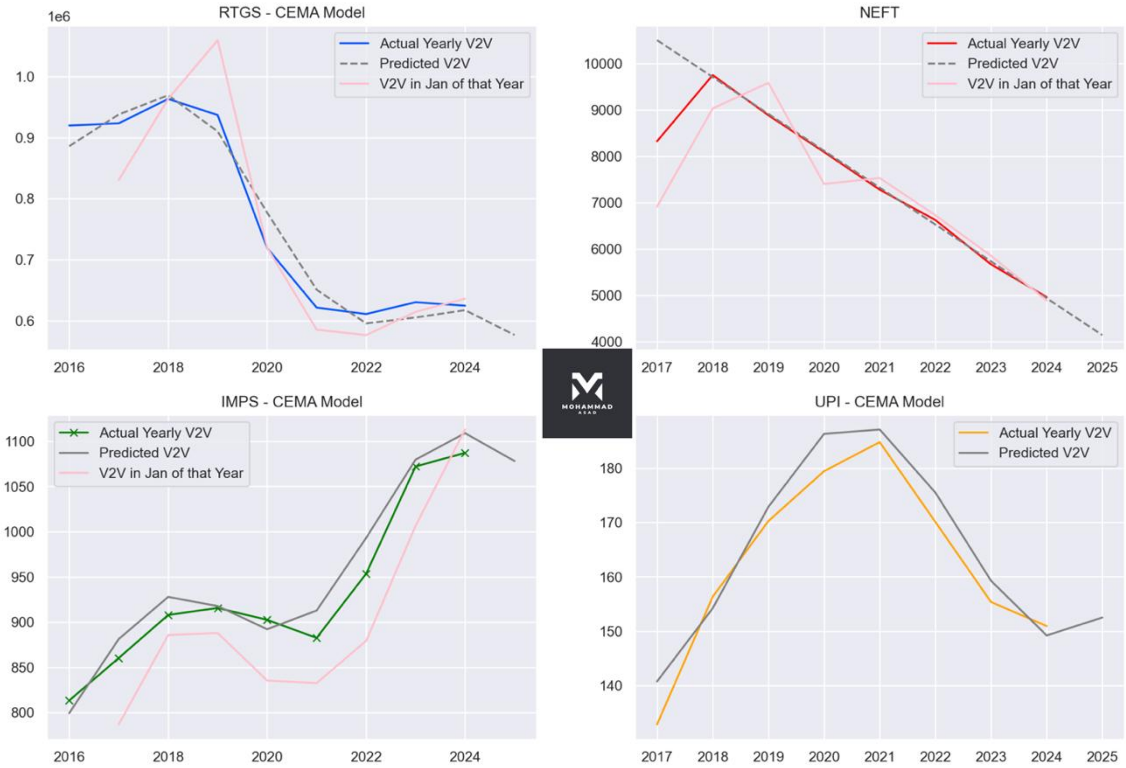

Fig 14: Actual Versus Forecasted Yearly Value Per Million (V2V)

Table 9 presents the forecast numbers computed using the models shown in Figure 14.

Table 9: Forecasted Yearly V2V

V2V	Model	2024	2025
RTGS	CEMA	617276.9	576562.9
NEFT	OLS	4940.87	4145.84
IMPS	CEMA	1108.97	1078.12
UPI	CEMA	149.23	152.52
V2V: Transaction value per million			

The yearly V2V equations for the models are as follows:

RTGS V2V CEMA Equation
V2V = ((Sin(Y)/(π1.85) +1) * (104459112.9576+ (-51329.7913*Y))) ∓ 3.2%**
From Year (Y) 2016 onward, ** is raised to power or ^.

NEFT V2V Equation
V2V = (1614081.0298 – 795.0297*Y) ∓ 0.687%
Year (Y) 2018–2030.

IMPS V2V CEMA Equation
V2V = ((Sin(Y*1.1)/(π2.45) +1) * (-59290.3598 + (29.8151*Y)) ∓ 1.96%**
From Year (Y) 2016 onward.

UPI V2V CEMA Equation
V2V = ((sin(Y*0.8)/(π1.75) +1) * (-2883.6671+ (1.5094*Y))) ∓ 2.52%**
From Year (Y) 2017 onward.

Now that yearly V2V equations have been established and the volume equations have been examined, I can derive annual transaction value equations by combining the two.

Volumes per Million (V2V) = Value ÷ Volumes;
=> V2V * Volumes = Value **Eq. (5)**

Next, the product of the actual volumes and V2V models was calculated and compared with actual transaction values. Similarly, the product of the volume equations from the Volumes section and V2V models was calculated, and the accuracy of these two V2V products was compared. **Eq. (6)**

The actual volume section in Table 10 refers to the transaction value obtained by combining the actual volume with our V2V equations. All results are within the 95% confidence level, and the error does not exceed 2.9%, which confirms the robustness and goodness of our V2V model fit. The timeline for testing these was based on the V2V model restrictions discussed in the equations.

Table 10: Errors (ϵ) of the transaction values forecasted.

	T(ϵ)	**%(ϵ)**	**Verdict**
From actual volumes			
IMPS	9.71E+00	1.95	☑☐
RTGS	-6.80E+00	2.88	☑☐
UPI	1.61E+01	2.7	☑☐
NEFT	4.62E-01	0.72	☑☐
From volume equations			
IMPS_OLS	2.40E+01	5.92	☑☐
RTGS_OLS	-9.11E+00	9.55	Average
UPI_OLS	2.80E+02	46.92	Useless
NEFT_OLS	3.80E+01	10.07	Below average
UPI2021_OLS	8.02E+00	4.01	☑☐
NEFT2021_OLS	3.28E+00	1.64	☑☐
RTGS_CEMA_YEARLY	-2.35E+00	4.5	☑☐
T(ϵ): Total sum of residual of the fitted data; ∓(ϵ): Positive or negative error percentage.			

The following section presents the transaction value obtained from the product of V2V and volume equations. *UPI_OLS* denotes the discarded model. *UPI2021_OLS* * V2V UPI and *NEFT2021_OLS* * V2V NEFT yielded results with 95% confidence. *RTGS_OLS* results are summed to yearly values, and obtaining a product with RTGS V2V yields average results. To improve this, the annual RTGS CEMA model (Eq. (9)), which, compared to *RTGS_OLS*, predicted the yearly volume results with nearly double accuracy or improved error rates, as the CEMA model for RTGS had 95% confidence and a 2.67% error. Consequently, it provided better results with the V2V RTGS.

RTGS Yearly Volumes(Y) CEMA Equation
Y = ((sin (Year*1.2)/(π-2.5) +1) * (-49219.94+ (24.4517*Year))) ∓ 2.67%**
From Year (Y) 2016 onward.

Eq. (9)

Initially, yearly values from the V2V product with actual volumes were obtained, followed by obtaining annual values from the V2V product with volume equations. Finally, RTGS CEMA model (Eq. (9)) provided the yearly RTGS volumes to improve the results (Table 10).

Importantly, the V2V models in Eq. (5)–(8) more accurately predict the transaction volume or value when the actual numbers for one of the variables are used to predict the other. Consequently, this V2V product method is less reliable when the actual numbers for both variables are unavailable. For intensive calculations and reliable forecasts of transaction values, the V2V product method is avoided when actual transaction volumes are unavailable. However, the V2V method is exceptionally reliable for describing the relationship between the transaction volumes and values.

6. Anticipated outcomes

This section presents important forecasts and expected outcomes based on the models developed in this study and the insights gained in this study.

- The yearly transaction value of the UPI platform in 2025 is projected to exceed Germany's GDP. This projection is made with a 95% confidence interval. According to the World Bank, Germany's real GDP (at constant prices) was 3.27 trillion USD in 2022 (World Bank Group 2023).
- UPI is expected to surpass 20 billion monthly transaction volume by mid-2026. This projection is made with 95% confidence.
- UPI is expected to process more than 29 billion monthly transactions by 2029.
- RTGS is expected to exceed 19 trillion USD annually by the end of 2024, with the annual transaction value likely reaching just 20 trillion USD. This projection is made with 95% confidence.
- IMPS is expected to exceed 1 trillion USD in total transaction value by 2026. This projection is with 90% confidence.
- UPI will surpass NEFT to become the second-largest public financial payment system in terms of transaction value by 2026. This projection is made with 95% confidence. This empirically asserts the sustainability of mobile payments in Indian financial systems.
- IMPS's yearly value per million is expected to vary from 2% to 3% from 2024 to 2026, with growth continuing for the next three years.
- NEFT is expected to show positive growth in total yearly volume by a minimum of 10% annually from 2024 to 2028, but its growth rate is expected to

decrease each subsequent year. This projection is made with 95% confidence.

- NEFT's V2V is expected to decrease by at least 10% annually from 2024 to 2028. This projection is with 98% confidence.

7. Discussion

This study has achieved significant milestones, offering actionable insights into major payment systems within the Indian context. By developing and employing the original CEMA models, it provides critical insights and reliable future projections into Indian fund-transfer mechanisms.

7.1 Key highlights

7.1.1. UPI dominance

This study establishes UPI as the leader in transaction volumes across all Indian payment systems, highlighting its transformative role in the digital payment landscape. UPI is expected to become the second-largest payment system by transaction value by the end of 2026, further reinforcing UPI's transformative role in India's financial infrastructure.

This study addressed sustainability and growth, highlighting UPI's potential to drive significant economic growth. Transaction volume and value demonstrate that UPI has established itself as a key pillar of India's economic infrastructure, though growth rates are expected to slow as it reaches the late majority of the adoption curve.

7.1.2. CEMA model efficacy

The original CEMA models' high confidence levels and low error rates offer a robust framework for modeling similar financial innovations in other emerging economies. This study address a critical gap in predictive modeling for Indian payment systems by providing precise curve fitting and robust quantitative insights. Notably, the novel CEMA models achieved the highest accuracy levels in predictive modeling in Indian payment system forecasting, underscoring their significant contribution to the literature on payment systems.

7.1.3. Comprehensive analysis

This study integrates historical statistics with new insights, such as UPI transaction clusters, and offers a comparative analysis of RTGS, NEFT, IMPS, and UPI within a unified framework.

7.2 Global impact, investment implications, and contributions

The predictive and CEMA models have significant implications for global finance and support the trend toward digital finance and cashless economies. This study is relevant to India and other underdeveloped economies worldwide and offers a foundational framework for future financial systems and research. Given the high level of accuracy required for modeling the various metrics of the payment system of a major economy, such as India, this study offers valuable insights for applying similar models in other emerging economies.

7.2.1. Direct and indirect investment implications

The growth of mobile payments in India is driven by UPI apps, such as Google Pay and PhonePe, which also present significant investment opportunities. UPI established itself as one of the pillars of the Indian economic and financial infrastructure in a short period. Concurrently, non-existent fintech players, including Google Pay and PhonePe, emerged as major mobile payment players within a few years. A growing middle-class economy has opened doors for fintech startups, infrastructure development, partnerships in digital wallets, and financial inclusion of products, funds, and remittances. Outside India, similar opportunities exist in developing nations with emerging mobile ecosystems where mobile payments can leapfrog traditional banking. Indian fintech models also have opportunities for international expansion, particularly in emerging economies. This indirectly affects investment management, portfolio strategies, and market dynamics. While primarily focused on facilitating digital transactions, these payment systems have broader implications for the financial ecosystem, which can influence investment strategies and market behavior. Global investment opportunities can be utilized by the following: 1) Fintech and payment infrastructure companies that facilitate digital payments, including wallet providers, transaction gateways, and cybersecurity solutions; 2) financial inclusion products that provide access to savings, stocks, and mutual funds for newly banked individuals and digital assets; 3) data analytics and AI firms leveraging mobile payment data for predictive analytics, consumer insights, and financial decision-making, as this study aimed for; and 4) cross-border payments and remittance services.

7.2.2. Investment and risk management implications

This study presents key forecasts that can principally help with investment strategies and risk management. First, the yearly transaction value on the UPI platform is projected to exceed 3 trillion USD, or the size of Germany's GDP, by 2025. This forecast informs private and public investment practitioners regarding the size of investment opportunities. Second, UPI processes more than 29 billion monthly transactions by 2029. This forecast informs high- and low-volume ticket investments, thus enabling better-informed investment strategies. Third, NEFT's V2V is expected to decrease by at least 10% annually from 2024 to 2028, whereas the UPI growth rate slows down as it reaches its maturity curve. This forecast provides a better risk assessment and management. Thus, the predictions of this study concerning the growth trends of payment systems can inform investment strategies, fintech innovations, and risk assessments.

Leveraging accurate forecasts provides opportunities to outperform market benchmarks by investing ahead of expected trends and helping in *alpha* generation. For instance, if transaction volumes (combining RTGS, NEFT, IMPS, and UPI) are expected to grow at higher rates than previous time periods, this can indicate positive interest in certain sectors or segments and investment opportunities. If the transaction volumes decline or grow at lower rates than previous time periods, it could signal an optimum time for hedging and help optimize investment hedge costs. Knowledge of transaction trends and transaction volumes enables better risk-reward assessments, which can help enhance *Sharpe ratios*.

Recent studies, such as those by Kröncke et al. (2021), suggest that monetary policy announcements significantly influence stock market movements, even in developed economies. Traditional models, which primarily focus on risk-free rates, explain only about 20% of these market fluctuations. The remaining 80% is driven by what are known as dark matter factors, which include shifts in investor behavior, changes in market sentiment, and latent elements such as liquidity effects and risk perceptions. These factors are not directly observed but play a crucial role in explaining short-term volatility, reflecting how investors adjust their portfolios and strategies in response to policy shifts. The present study complements this understanding by emphasizing the role of transaction volumes as a critical metric for assessing market liquidity and forecasting economic trends. By analyzing transaction volumes, the study provides valuable insights into how liquidity shifts can amplify or dampen the effects of policy changes, thus offering a more complete picture of market dynamics during periods of heightened volatility.

For example, understanding transaction growth can help identify sectors poised for expansion or signal areas that may need hedging. This is particularly important as transaction volumes are directly linked to market liquidity, which influences asset prices and trading costs. By integrating liquidity metrics with the dark matter factors identified in previous research, this study offers a more robust framework for understanding both the immediate market responses to monetary policy events and the longer-term dynamics that shape investment opportunities and risk management strategies. Together, these complementary approaches provide a more nuanced and comprehensive view of market behavior, allowing investors to optimize their portfolio strategies and navigate complex economic environments more effectively. In doing so, the study reinforces the concept of risk shifts, discussed in earlier work, by using transaction volumes to better capture the liquidity-driven components of market responses.

Thus, these predictions can help identify entry and exit points, minimizing draw-downs and maximizing gains. Transaction volume is a direct indicator of market liquidity. A higher expected volume growth suggests assets can be bought or sold with minimal price impact, facilitating efficient hedging. Large hedge positions in illiquid markets may move the market, leading to unfavorable execution prices. It aids in risk management, reducing hedging costs, and offering derivative potential for investors, researchers, and academics. It can forecast countries' market sentiment, inform trends, and provide insights for researchers, practitioners, and policymakers. This study also serves as a tool for gauging economic activity, trends, and signals of economic expansion or contraction. It provides practitioners with leading indicators through CEMA models to simulate a stable economic instrument, gauge momentum, and inform interest rate decisions for financial stability.

7.3 Limitations and future research

7.3.1. Limitations

First, this study does not explicitly focus on how these payment systems directly impact investment management, portfolio strategies, or market dynamics. Therefore, future studies could explore the impact of the prominent market factors of each country on the use of transaction volumes to forecast sentiments and analyze markets. The transaction volume of payment systems can be misleading if used in isolation for market forecasts. For instance, higher growth in payment transaction volumes in forecasts indicates that some sectors or segments will gain momentum, indicating the opportunity without specifying the sector or segment. Accordingly, market investment practitioners should exercise caution when considering the proper context of forecasts and insights. Second, these models were developed based on mathematical factors influenced by the nature of these payment systems. Consequently, the confidence intervals of the model depend on policy changes. For instance, the maximum daily limit for a UPI transaction is INR 1,00,000 (approximately USD 2,424). Still, if this were to be modified in the future, it would induce changes in transaction values. However, the central modeling idea remains viable. Because of the robustness of the current models, confidence intervals, and diversity of metrics, these models would only need to be fine-tuned to align with new policies and retain their accuracy.

7.3.2. Future research

Future studies aiming to build on this study's findings could explore the long-term impacts of digital payment systems on broader economic factors, investigate the scalability of UPI-like systems in other countries, and refine predictive models to adapt to evolving financial landscapes. A new avenue for comparative analysis can include national cryptocurrencies or central bank digital currencies, which many countries are undertaking. Additionally, mainstream store-of-value and transfer-of-value cryptocurrency blockchains, such as Bitcoin, can also be part of comparative analysis in economies increasingly pushing the boundaries of digital finance and fund transfer mechanisms. One case in point is El Salvador, where Bitcoin is now tightly integrated into the national economic and financial infrastructure. Essentially, what India is pursuing with UPI, El Salvador is with Bitcoin. With growing investments in digital currency and payment systems, this study will continue to grow in relevance.

The developed models serve as a foundation for future economic research, enabling the exploration of both the long- and short-term impacts on the broader economy and their interaction with other financial technologies. This study's contributions demonstrate significant empirical advancement in global finance and financial systems and could foster similar economic development internationally.

8. Conclusion

The study on leveraging predictive financial modeling and comparative research for economic forecasting through India's payment systems demonstrates the transformative role of digital payment infrastructures in shaping modern economic activities and financial inclusion. The analysis of RTGS, NEFT, IMPS, and UPI transaction systems revealed that the rapid growth of digital payments has become a significant indicator of economic expansion, technological adoption, and consumer behavioral transformation in India. Comparative evaluation of payment systems highlighted that UPI and IMPS experienced exceptionally high growth due to increasing smartphone penetration, government-led digital initiatives, enhanced fintech ecosystems, and the rising preference for real-time and cashless transactions. The predictive modeling approaches applied in the study, particularly Random Forest regression and linear regression techniques, provided meaningful insights into transaction trends, forecasting accuracy, and system performance. The Random Forest model achieved considerably higher predictive capability across most payment systems compared to linear regression, indicating that nonlinear and machine learning-based approaches are more suitable for forecasting complex financial transaction behaviors. The study also identified that traditional linear models were inadequate in capturing rapidly evolving digital payment dynamics, especially after the post-pandemic acceleration in electronic transactions. Furthermore, the findings emphasize that transaction growth patterns in RTGS and NEFT continue to reflect institutional and high-value financial activities, whereas IMPS and UPI represent retail-driven digital transformation and widespread public adoption. The integration of predictive analytics into payment system evaluation offers policymakers, financial institutions, fintech companies, and economic planners a strategic framework for understanding future transaction behavior, identifying financial risks, and improving digital financial governance. The research further contributes to the growing literature on fintech-driven economic forecasting by demonstrating how payment system datasets can act as reliable indicators of macroeconomic and financial sector development. In addition, the study highlights the importance of robust digital infrastructure, cybersecurity mechanisms, regulatory innovation, and financial literacy programs in sustaining long-term digital payment growth. Overall, the research concludes that predictive financial modeling combined with comparative analysis of payment systems can significantly improve economic forecasting accuracy, support evidence-based policy formulation, strengthen digital financial ecosystems, and accelerate India's transition toward a technologically advanced and inclusive digital economy.

Statements and Declarations

1. **Availability of data and materials:** Data and code can be made available upon request.
2. **Competing Interest:** None.
3. **Funding:** Not applicable.
4. **Ethics approval:** Not applicable; the study did not involve any human subjects.

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