Forecasting of UPI Payment Services Demand in India Using Machine Learning Techniques

Dr. Vengalarao Pachava
Assistant Professor,
School of Business Management,
NMIMS University Jadcherla Campus
Email: vengalarao.pachava@nmims.edu

Dr. Siva Krishna Golla
Assistant Professor,
School of Management Studies,
National Forensic Sciences University,
Gandhinagar, Gujarat.
Email: sivakrishna.golla@nfsu.ac.in

Prof. Kavitha A Karkera
Associate Professor,
School of Management MBA,
Nagarjuna Degree College, Bengaluru,
Email: kavithakarkera@nagarjunadegreecollege.in

Dr. Abhilash Ponnam
Associate Professor,
School of Business Management,
NMIMS University Jadcherla Campus
Email: abhilashponnam@gmail.com

Abstract

Unified Payments Interface (UPI) is a technology that integrates several bank accounts into a single mobile app (of any participating bank), combining many banking services, smooth money transfer, and merchant payments under one umbrella. Because of demonetization and the Covid-19 outbreak, UPI payments have changed and increased significantly, becoming a key element of the Indian payment system. In 2022 financial year, it processed over 45 billion transactions worth over Rs.83 lakh crore. The Auto Regressive Integrated Moving Average (ARIMA) approach is well-known for predicting time series data while taking into account the non-linearity of the data. Since 2016, both the total number of transactions and the total value of transactions in the UPI system have been steadily growing. Using the ARIMA time series approach, this research forecasted the future one-year value and volume of UPI payments. The findings of this study indicate that there will a rapid growth in the use of UPI for digital transactions, large number of payments settled through the UPI platform, the trend would continue for the next calendar year.

Keywords: Unified Payments Interface, ARIMA, Banking and Time Series

Introduction

The Indian banking sector constantly evolving, and a major impetus came from the nationalization of commercial banks with social objectives; consequently, it has been witnessing a wide range of policy-induced reforms and structural changes since the early 1990s (Gupta, 2021). The nationalization of commercial banks with social objectives was a major impetus for the evolution of the Indian banking sector. The banking industry has undergone a significant shift as a result of the tremendous development made in the area of information technology(Bhuyan et al., 2021). Telecommunication and electronic data processing advancements have pushed these transformations even farther forward. The banking and financial industries throughout the world have been completely transformed as a result of automation(Usmonova Durdona Shukhratovna, 2021). Click-and-order banking channels such as online banking, automated teller machines, tele-banking, and mobile banking are becoming more popular alternatives to traditional brick-and-mortar bank branches. A few clicks are all it takes for customers to access their accounts, check their statements and move payments(Kaur et al., 2021). Due to technological advancement, availability of ICT infrastructure, improve of basic education and a sudden effect of covid 19 pandemic caused for rapid usage of e-banking features in India(Ahmed & Sur, 2021). According to a study conducted on mobile payment services such as mobile wallets and mobile banking during India's demonetization, the majority of urban youth have adopted mobile payment methods (Chopra, 2017). Immediate Payment Service (IMPS) transaction value grew by 196.7 percent year-on-year in January 2017. In December 2016, NACH (National Automated Clearing House) fund clearing platform set up by NPCI has grew 116.7%. (Sinha et al., 2019). Mobile payment penetration increased in India after the demonetization of high-value currency notes; however, usage and retention remain low; the primary reason for this is the privacy concerns associated with mobile banking. All this analysis reveals that demonetization boosted digital payments immediately, but not long-term (Chakrabarty et al., 2020).

Electronic banking, sometimes known as e-banking, is a product of globalisation, increased competition, and the explosive rise of information technology systems. It has evolved into a self-service delivery channel that enables banks to give information and services to their clients in a more convenient manner using a variety of technological services like as the Internet and mobile phones (Kurnia et al., 2010). Electronic funds transfer for retail purchases, automatic teller machines (ATMs), and automatic payroll deposits and bill payments are some of the features of e-banking. RBI initiative in India has achieved steady growth in E–Payments during the last ten years. Many e-payments systems have been developed to date in order to digitalize the current banking system. One of them is UPI (Unified Payment Interface) introduced by National Payments Corporation of India (NPCI) in the year of 2016, with the goal of simplifying, streamlining, and enhancing the security of the electronic banking sector. NPCI bringing change in all electronic payments made in India, its guidance and support by the Reserve Bank of India (RBI) and the Indian Bank Association (IBA) provided a Unified Payments Interface (UPI) system by which 24*7 payments are made easy, real-time, and frictionless (Rai et al., 2017.).

Unified Payments Interface (UPI) has secured immense recognition, a convenient device like smart phone used for diversified financial transactions. Direct transactions of payment and receipts rightly made using a virtual payment address on the UPI platform. For using a UPI interface, it is mandatory to have a Bank account and link it with the UPI application. Google Pay, Phonepe, Whatsapp Pa, Amazon Pay are a few UPI applications frequently used for a wide variety of financial transactions. The rapid advancement in the use of Unified Payment Interface has opened the gateway for most of the banks to provide this service in their mobile applications (A & Bhat, 2021). Since UPI is linked to a bank account, no wallet is needed, your bank account can be used to link UPI, customers can use any bank or third-party app with UPI's compatibility across all systems. Some of the most important factors for the success of UPI are simplicity, adoption, security and cost (Shree et al., 2021).

UPI is widely accepted as a user-friendly interface for digital settlement of transactions. UPI has eliminated the multiple mediators in the settlement of financial transaction, thereby increasing its acceptance (A & Bhat, 2021). The easy access to smart phones, the convenience of identity verification online, universal access to banking and introduction of biometric sensors in phones has encouraged the positive attitude to the acceptance of UPI for promoting a less-cash culture in India (K. Devi & Devadutta Indoria, 2021). The popularity will increase for future payments, considering its convenience, safety and minimal cost. The recognition of digital payments expected to increase in line with the overall socioeconomic development of the population (Shree et al., 2021). With the forethought to encourage cashless Indian economy, UPI has helped people tremendously in transfer of funds instantly with much ease (Madwanna et al., 2021).

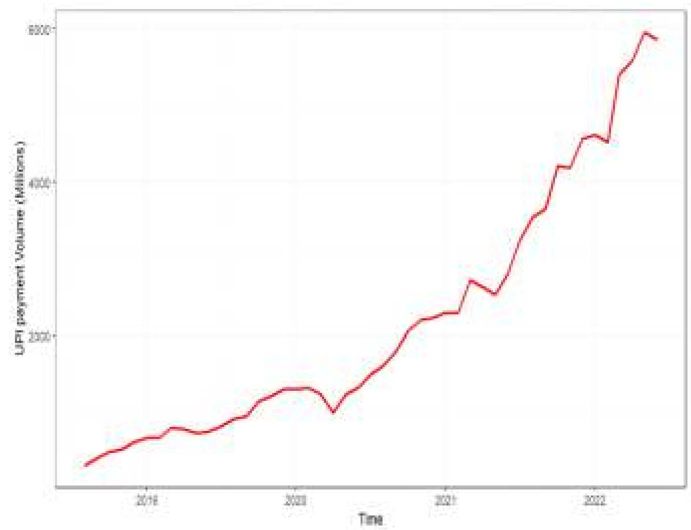
Time series analysis is a specialised method of examining a set of data points gathered over a specified period of time. In time series analysis, data points are recorded at regular intervals throughout a predetermined length of time rather than being recorded randomly or irregularly. However, this form of analysis is not just the collection of data over a long period of time(Katris, 2021). The increased availability of data that is not steady has made prediction analysis more difficult. Researchers and academics are still determining the optimal approach in finance and economics to overcome this obstacle. The prediction theory prompted academicians to create several prediction models such as artificial neural networks, hybrid models, and ARIMA models(Khandelwal et al., 2015). The assumption that the underlying model is linear is what makes ARMA difficult to apply to a wide variety of complex real-world time series, despite the fact that it has been quite successful. Autoregressive integrated moving average (ARIMA) is an extension of ARMA that can deal with nonstationary time series forecasting by using differencing methods to handle this challenge(Kotu & Deshpande, 2019). Differentiating approaches may be used to reduce the effects of trend components before fitting an ARIMA model when the data contain trend and heteroscedasticity. However, the vast majority of currently available ARIMA models continue to have severe shortcomings, including low accuracy, high error rate, handling non linear data etc. But still ARIMA models using vastly in many of the domains to forecast the future values. Time series forecasting has played a key role in a variety of disciplines throughout the last several decades, including stock markets (Shah et al., 2022), daily and monthly weather forecasting (Alsharif et al., 2019), crop production forecasting (Mishra et al., 2021), disease cases prediction in medical field(Liu et al., 2016), sales prediction (Prasanth Shakti et al., 2017) , production value in mechanical industry(Liang, 2009), oil production prediction (Ning et al., 2022), financial budget forecasting(Rhanoui et al., 2019) etc.

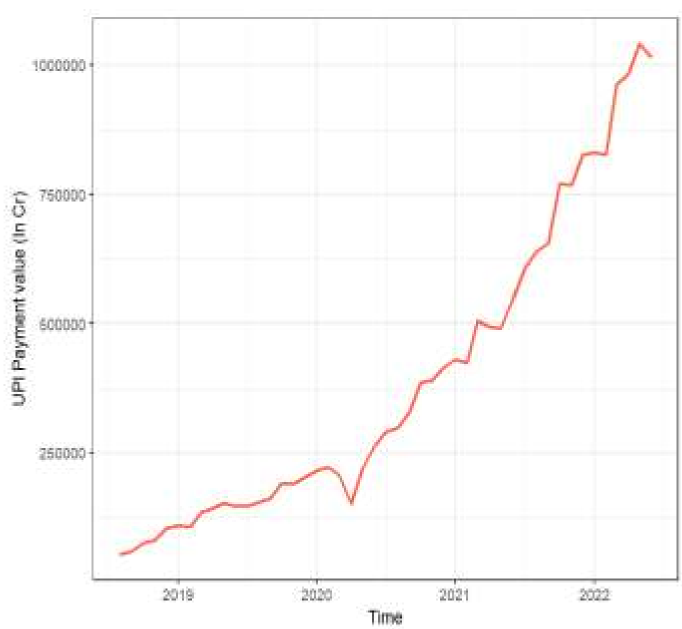
During the fiscal year (FY) 2021-22, the unified payments interface approach successfully processed payments totalling $1.09 trillion and another key milestone in the month of March 2022 it has completed 5.04 billion transactions. Because of the focus that institutions put on decision making and strategy making predicting is the key, predicting the UPI transactions value and volume of data has become a popular topic of conversation for a diverse range of individuals for digital transformation of money.

Data

UPI payments monthly transaction value (in crore) and volume (in million) data were acquired from the internet repository of the National Payments Corporation of India. The actual data is available from 2016 august to 2022 June. However, for the purpose of this study, the researchers used the data from 2018 august to 2022 June in order to omit self-transactions data from 2016 august to 2018 august.

Figure 1: UPI payment volume and value





Methodology

Box - Jenkins analysis is a systematic approach of discovering, estimating, validating, and applying integrated autoregressive, moving average (ARIMA) time series models that was used in this study. This approach is suitable for use with time series that are of medium to long duration of the data points like at least 50 observations are required.

Model Identification

In order to identify the model, the first step is to ensure that the data exhibit stationarity properties. These features ensure that the mean, variance, and autocorrelation structure do not vary over a period.

$$E(y_t) = \mu \quad \forall t(\text{Mean})$$

$$Var(y_t) = \sigma_y^2 \quad \forall t(\text{Variance})$$

$$cov(y_t, y_{t-1}) = \gamma_j(\text{Auto-correlation})$$

Decomposition technique used to identify the data stationarity properties; it consists of four subplots, which explains about the data at level, trend, seasonality and noise in the data. If trend and seasonality presented in the data that can be considered as non-stationarity. However, the autocorrelation function indicates the relationship between the present time value and its own lagged time values. If the data exhibits a trend, the autocorrelation function's lag values can rise from low to high, whereas if the data exhibits seasonality, the function's lag values can display systematic fluctuations in the graph.

$$ACF(n) = \frac{cov(x_t, x_{t-n})}{var(x_t)}$$

Partial autocorrelation function find the correlation between current time value with its past lag values where it controls the between values effect.

$$PACF(n) = Corr\left[x_t - E * \left(x_t | x_{t-1} \ldots x_{t-n+1}\right), x_{t-n}\right]$$

There are three major components are there in ARIMA model, those are Auto Regressive (AR), Integrated (I) and Moving Average (MV). This three components are represented as p,d,q value in the model which are representing AR (p),I(d) and MA(q).

AR(p) components used to predict the current time values with its own past time lag values.

$$y_t = c + \beta_1 y_{t-1} + \beta_2 y_{t-2} \ldots + \beta_p y_{t-p} + \varepsilon_t$$

I (d) Differenced lag value of the data

First order differencing

$$y_t' = y_t - y_{t-1}$$

Second order differencing

$$y_t'' = y_t' - y_{t-1}'$$

MA (q) components used to predict the current time values with its own past error lag values.

$$y_t = c + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} \cdots + \theta_q \varepsilon_{t-q}$$

ACF graph is useful to estimate the MA components lag values and PACF component useful to estimate the AR component.

Model Development:

The ACF and PACF value models were used to identify the suitable p,d,q values for predicting future values. This research examined several p,d,q value combinations to find the best model that met all of the assumptions. This study used Akaike's information criterion (AIC), Bayesian information criterion (BIC), and maximum log likelihood values to identify the best model from the available combinations. The optimal model for predicting time series values is one that has a low AIC value and a high log likelihood value.

AIC = -2/N * LL + 2 * k/N

BIC = -2 * LL + log(N) * k

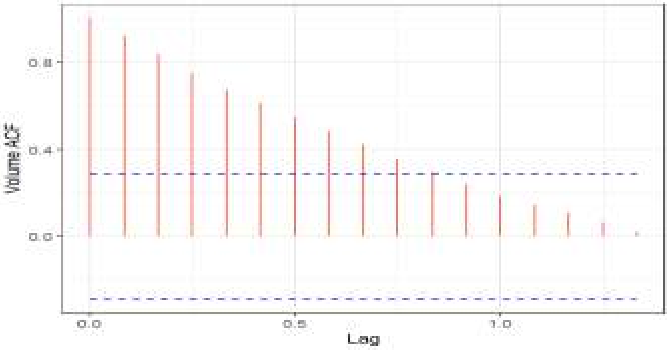
Model Validation

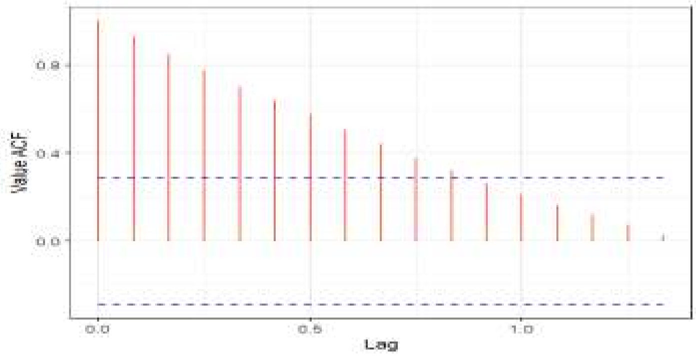
The assumption that there is no autocorrelation and that the distribution of the residual values follows a normal (Gaussian) distribution. In order to investigate such assumptions, this research made use of the Ljung-Box test statistic in conjunction with the autocorrelation function (ACF) of the residuals. The Kolmogorov-Smirnov normality test and the arch test used to assess normality and heteroscedasticity, respectively.

Results and Discussion

The data stationarity is a fundamental quality in the box-Jenkin approach. Initially, this study verified the data stationarity using ACF graphs of the volume and value of UPI payments. The ACF plots revealed a declining pattern of correlation between the data and its very own lag values. This indicates that the data did not adhere to stationary qualities.

Figure 2: ACF plots of UPI payment volume and value





The differencing method used in order to transform this non-stationary data into stationary form; in the second differencing, the data transformed into stationary form in terms of both its volume and its value. Statistical verification of data stationarity conducted using the ADF test.

H0: Unit root presented in the data

H1: Unit root not presented in the data

The results of the ADF test statistic p value for the UPI value of 0.0001 and the UPI volume of 0.01474 shown that the null hypothesis rejected, which indicates that the data demonstrates stationarity at both differencing levels.

Table 1: ARIMA model for UPI payment value and volume

		Volume			**Value**		
Characteristics		**(0,2,2)**	**(2,2,1)**	**(1,2,1)**	**(0,2,2)**	**(1,2,2)**	**(2,2,1)**
AR(1)	**α_1**		-0.2599	-0.2449		0.6263	-0.3579
	SEB		0.1746	0.1594		0.1302	0.1688
	Z Value		-1.4884	-1.5370		4.8099	-2.1197
	P value		0.1366	0.1240		0.0000	0.0340
AR(2)	**α_2**		-0.0351				-0.1439
	SE		0.1688				0.1640
	Z Value		-0.2077				-0.8773
	p value		0.8354				0.3800
MA(1)	**$Ø_1$**	-1.1226	-0.8482	-0.8557	-1.2852	-1.9351	-0.8414
	SE	0.1587	0.0840	0.0737	0.1672	0.1713	0.0797
	Z Value	-7.0743	-10.0918	-11.6150	-7.6857	-11.2940	-10.5530
	p value	0.0002	0.0000	0.0000	0.0000	0.0000	0.0000
MA(2)	**$Ø_2$**	0.2423			0.3974	0.9963	-0.8414
	SEB	0.1527			0.1619	0.1758	0.0797
	Z Value	1.5863			2.4543	5.6670	-10.5530
	p value	0.1127			0.0141	0.0000	0.0000
AIC		608.2100	610.3200	608.3600	1071.0000	1071.0400	1073.7200
Log likelihood		-301.1000	-301.1600	-301.1800	-532.5000	-531.5200	-532.8600
RMSE		186.8556	187.1650	187.2910	31827.0000	29823.6000	32138.0000
MAPE		6.7453	6.7001	6.6638	6.6774	6.5519	6.6367

A number of models were examined with several iterations of p, q values in order to build a model that takes stationarity data into consideration. The AIC and log likelihood values were used to identify which three top models should be chosen for the final comparison. Table 1 provides an overview of the several UPI payment volume and value models that available. The ARMA (0,2) model was selected for forecasting purposes for the UPI payments volume data because, out of all the models, this model had the lowest AIC value (608.21), and all of the coefficient values were determined to be significant. Additionally, this model was the only model in which all of the coefficient values were significant. The ARMA(1,2) model was selected for the UPI payments value data because it has the AIC value (1071.04), which was the lowest of all the models, and all of its coefficient values are significant. Model residual autocorrelation tested with Ljung boxt test, where both UPI value and volume models residuals were not indicating any significant auto correlation presented in the model. Table 2 indicates the model fit values generated through Ljung box test. Test statistic p values greater than .05, where failed to reject null hypothesis can be conclude that both the models were fit.

H0: Model doesn't show lack of fit

H1: Model shows lack of fit

Table 2: Ljung box model fitness test.

Model	Test Type	Chi-square	Df	p-value	Decision
Volume	Ljung Test	23.866	24	0.4693	Accepted
Value	Ljung Test	32.277	24	0.1203	Accepted

Both models projected over the next two years, and by June 2024, the forecasting graphs indicate a clear increase trend for both UPI payments volume and value. The expected value and volume of UPI payments are shown in Table 3. The volume of UPI transactions expected to expand from 5.86 billion per month to 11.41 billion by the end of June 2024. The value of UPI transactions is expected to rise from 1014384 crore to 2029901 crore rupees by the end of June 2024. This is approximately two times the value of the current month, which suggests tremendous growth in the months to come.

Table 3: UPI payments forecasted value and volume

		Volume			Value		
Month	**Year**	**Point Forecast**	**Lo 95**	**Hi 95**	**Point Forecast**	**Lo 95**	**Hi 95**
Jul	2022	6169.312	5795.03	6543.59	1070415	1009574	1131257
Aug	2022	6397.368	5899.45	6895.29	1120677	1045534	1195819
Sep	2022	6625.425	6003.18	7247.67	1167325	1083490	1251160
Oct	2022	6853.481	6103.89	7603.07	1211709	1120289	1303130
Nov	2022	7081.537	6200.61	7962.46	1254677	1155010	1354343
Dec	2022	7309.594	6292.92	8326.27	1296756	1187234	1406279
Jan	2023	7537.65	6380.63	8694.67	1338280	1216753	1459807
Feb	2023	7765.706	6463.69	9067.72	1379455	1243529	1515381
Mar	2023	7993.763	6542.11	9445.41	1420412	1267658	1573167
Apr	2023	8221.819	6615.94	9827.7	1461233	1289310	1633156
May	2023	8449.876	6685.25	10214.5	1501968	1308693	1695244
Jun	2023	8677.932	6750.11	10605.8	1542650	1326008	1759291
Jul	2023	8905.988	6810.6	11001.4	1583298	1341443	1825152
Aug	2023	9134.045	6866.81	11401.3	1623925	1355159	1892690

		Volume			Value		
Month	**Year**	**Point Forecast**	**Lo 95**	**Hi 95**	**Point Forecast**	**Lo 95**	**Hi 95**
Sep	2023	9362.101	6918.83	11805.4	1664538	1367293	1961784
Oct	2023	9590.157	6966.72	12213.6	1705144	1377962	2032326
Nov	2023	9818.214	7010.57	12625.9	1745744	1387263	2104226
Dec	2023	10046.27	7050.46	13042.1	1786342	1395277	2177407
Jan	2024	10274.326	7086.46	13462.2	1826937	1402074	2251800
Feb	2024	10502.383	7118.63	13886.1	1867531	1407713	2327348
Mar	2024	10730.439	7147.05	14313.8	1908124	1412246	2404001
Apr	2024	10958.496	7171.78	14745.2	1948716	1415718	2481715
May	2024	11186.552	7192.88	15180.2	1989309	1418166	2560451
Jun	2024	11414.608	7210.41	15618.8	2029901	1419627	2640174

Figure 3: UPI payment forecasted volume

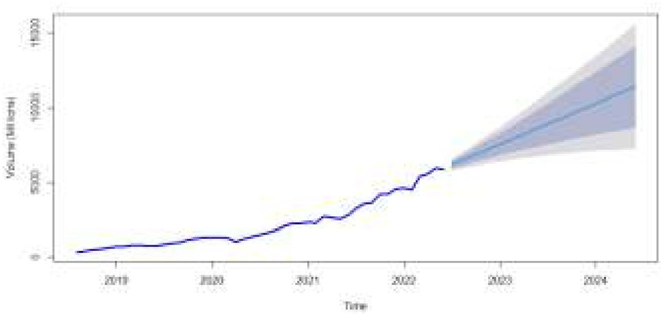
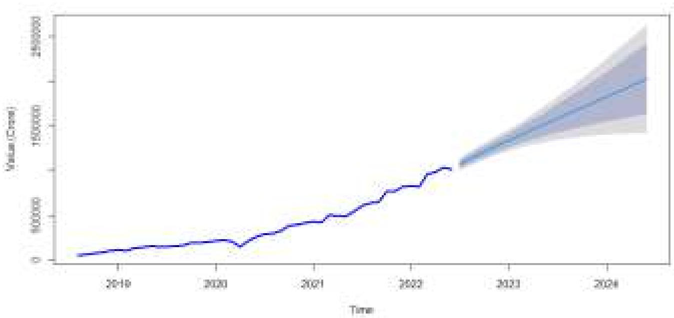


Figure 4: UPI payment forecasted value



Conclusion:

UPI payments have risen to prominence in India's banking system because of demonetization, the increase of ICT infrastructure, rising income levels, and the spread of the pandemic. (A. & S., 2022). During the pandemic, the majority of people in the country chosen to pay their bills using UPI transactions, therefore the majority of people familiar with the system (Chakraborty et al., 2022). According to the findings of this study, there will be a generally favourable trend toward the number of UPI payments and the value of transactions during the course of the next calendar year. This is clearly indicate the upcoming challenge to the digital payment system due to huge number of transactions and related failures of the transaction. National Payment Corporation of India data shows that UPI payments were faced significant errors while sending and receiving money during transactions (UPI Report,2022). Recent studies found that most of the banks UPI payments transactions are facing technical errors during the peak time of the payments (Donda et al., 2022). Banks need to update their IT infrastructure as the growing demand from the customers to avoid the transaction failures during peak time. Some of the studies identified the key security challenges in UPI payments system where customers lost their money due to cyber frauds (Chaterji & Thomas, 2017; Chawla et al., 2021). The conclusions of this study are consistent with findings of previous studies (A & Bhat, 2021; K. Devi & Devadutta Indoria, 2021; Panse et al., 2021) that have been undertaken on the growth of digital payment systems in other countries, including India. There is a rapid growth in the use of UPI for digital transactions, large number of payments settled through the UPI platform, the trend would continue for the next calendar year. India is in the forefront of a comprehensive progress in digital payments and UPI is the harbinger in this step towards digitization of transactions. To maintain the growing trend of UPI payments in India, the government and other regulatory organizations must concentrate on the pit fall of UPI payment systems (Galhotra et al., 2021; Madwanna et al., 2021; Yogesh Chandra & Kapil, 2021) and implement remedial measures to meet the demand.

References

- A, M., & Bhat, G. (2021). Digital Payment Service in India - A Case Study of Unified Payment Interface. https://doi.org/10.5281/ZENODO.5091207
- A., M., & S., G. B. (2022). India's Digital Payment Landscape – An Analysis. International Journal of Case Studies in Business, IT and Education (IJCSBE), 6(1), 223–236. https://doi.org/10.47992/IJCSBE.2581.6942.0161
- Ahmed, S., & Sur, S. (2021). Change in the uses pattern of digital banking services by Indian rural MSMEs during demonetization and Covid-19 pandemic-related restrictions. Vilakshan - XIMB Journal of Management, ahead-of-print(ahead-of-print). https://doi.org/10.1108/XJM-09-2020-0138
- Alsharif, M. H., Younes, M. K., & Kim, J. (2019). Time Series ARIMA Model for Prediction of Daily and Monthly Average Global Solar Radiation: The Case Study of Seoul, South Korea. Symmetry 2019, Vol. 11, Page 240, 11(2), 240. https://doi.org/10.3390/SYM11020240
- Bhuyan, B., Patra, S., & Bhuian, R. K. (2021). Measurement and determinants of total factor productivity: evidence from Indian banking industry. International Journal of Productivity and Performance Management, ahead-of-print(ahead-of-print). https://doi.org/10.1108/IJPPM-06-2019-0256/FULL/XML
- Chakrabarty, M., Jha, A., & Ray, P. (2020). Demonetization and digital payments in India: perception and reality. Https://Doi.Org/10.1080/13504851.2020.1752895, 28(4), 319–323. https://doi.org/ 10.1080/13504851.2020.1752895
- Chakraborty, D., Siddiqui, A., Siddiqui, M., Rana, N. P., & Dash, G. (2022). Mobile payment apps filling value gaps: Integrating consumption values with initial trust and customer involvement. Journal of Retailing and Consumer Services, 66, 102946. https://doi.org/10.1016/J.JRETCONSER.2022.102946
- Chawla, A., Manjhi, G., & Bhattacharya, G. (2021). Implications of Banking Regulations on Online Payment Failures.
- Chaterji, Dr. A., & Thomas, R. (2017). Unified Payment Interface (Upi) a Catalyst Tool Supporting Digitalization – Utility, Prospects &Amp; Issues. South Dakota Review, 50(SPEC.ISSU.), 74–79. https://doi.org/10.5040/9781408169827.00000010
- Chopra, R. (2017). Impact of Demonetization on Indian Economy. Global Journal of Enterprise Information System. https://doi.org/10.18311/gjeis/2017/15857
- Donda, R., Arpana, M., Rajesh, D., Sagar, M. A., & Roshitha, N. (2022). Users Perceptions and Problems on Mobile Wallet Payments-A Study in Visakhapatnam City. ComFin Research, 10(1), 12–16. https://doi.org/10.34293/commerce.v10iS1-Jan.4750
- Galhotra, B., Jatain, A., Bajaj, S. B., & Jaglan, V. (2021). Mobile Payments: Assessing the Threats, Challenges and Security Measures. Proceedings of the 5th International Conference on Electronics, Communication and Aerospace Technology, ICECA 2021, 997–1004. https://doi.org/10.1109/ICECA52323.2021.9676092
- Gupta, R. (2021). Industry 4.0 Adaption in Indian Banking Sector—A Review and Agenda for Future Research: Https://Doi.Org/10.1177/0972262921996829. https://doi.org/10.1177/0972262921996829
- K. Devi, & Devadutta Indoria. (2021). Digital Payment Service In India: A Review On Unified Payment Interface. International Journal of Aquatic Science. http://www.journal-aquaticscience.com/article_136176.html

- Katris, C. (2021). A time series-based statistical approach for outbreak spread forecasting: Application of COVID-19 in Greece. Expert Systems with Applications, 166, 114077. https://doi.org/10.1016/J.ESWA.2020.114077
- Kaur, S. J., Ali, L., Hassan, M. K., & Al-Emran, M. (2021). Adoption of digital banking channels in an emerging economy: exploring the role of in-branch efforts. Journal of Financial Services Marketing, 26(2), 107–121. https://doi.org/10.1057/S41264-020-00082-W/TABLES/3
- Khandelwal, I., Adhikari, R., & Verma, G. (2015). Time Series Forecasting Using Hybrid ARIMA and ANN Models Based on DWT Decomposition. Procedia Computer Science, 48(C), 173–179. https://doi.org/10.1016/J.PROCS.2015.04.167
- Kotu, V., & Deshpande, B. (2019). Time Series Forecasting. Data Science, 395–445. https://doi.org/10.1016/B978-0-12-814761-0.00012-5
- Kurnia, S., Peng, F., & Liu, Y. R. (2010). Understanding the adoption of electronic banking in China. Proceedings of the Annual Hawaii International Conference on System Sciences. https://doi.org/10.1109/HICSS.2010.421
- Liang, Y. H. (2009). Combining seasonal time series ARIMA method and neural networks with genetic algorithms for predicting the production value of the mechanical industry in Taiwan. Neural Computing and Applications, 18(7), 833–841. https://doi.org/10.1007/S00521-008-0216-0/TABLES/5
- Liu, L., Luan, R. S., Yin, F., Zhu, X. P., & Lü, Q. (2016). Predicting the incidence of hand, foot and mouth disease in Sichuan province, China using the ARIMA model. Epidemiology & Infection, 144(1), 144–151. https://doi.org/10.1017/S0950268815001144
- Madwanna, Y., Khadse, M., & Chandavarkar, B. R. (2021). Security Issues of Unified Payments Interface and Challenges: Case Study. ICSCCC 2021 - International Conference on Secure Cyber Computing and Communications, 150–154. https://doi.org/10.1109/ICSCCC51823.2021.9478078
- Mishra, P., Yonar, A., Yonar, H., Kumari, B., Abotaleb, M., Das, S. S., & Patil, S. G. (2021). State of the art in total pulse production in major states of India using ARIMA techniques. Current Research in Food Science, 4, 800–806. https://doi.org/10.1016/J.CRFS.2021.10.009
- Ning, Y., Kazemi, H., & Tahmasebi, P. (2022). A comparative machine learning study for time series oil production forecasting: ARIMA, LSTM, and Prophet. Computers & Geosciences, 164, 105126. https://doi.org/10.1016/J.CAGEO.2022.105126
- Panse, C., Sharma, A., Bhimavarapu, V. M., Rastogi, S., & Mrudula Bhimavarapu, V. (2021). Unified Payment Interface (UPI): A Digital Innovation and Its Impact on Financial Inclusion and Economic Development. Universal Journal of Accounting and Finance, 9(3), 518–530. https://doi.org/10.13189/ujaf.2021.090326
- Prasanth Shakti, S., Kamal Hassan, M., Zhenning, Y., Caytiles, R. D., & NChSN, I. (2017). Annual Automobile Sales Prediction Using ARIMA Model. International Journal of Hybrid Information Technology, 10(6), 13–22. https://doi.org/10.14257/ijhit.2017.10.6.02
- Rai, K. A., Somaiya, K. J., & Rajvaidya, R. (n.d.). THE ADOPTION OF M-WALLET IN INDIA.
- Rhanoui, M., Yousfi, S., Mikram, M., & Merizak, H. (2019). Forecasting financial budget time series: ARIMA random walk vs LSTM neural network. IAES International Journal of Artificial Intelligence (IJ-AI, 8(4), 317–327. https://doi.org/10.11591/ijai.v8.i4.pp317-327
- Shah, H., Bhatt, V., & Shah, J. (2022). A Neoteric Technique Using ARIMA-LSTM for Time Series Analysis on Stock Market Forecasting. 381–392. https://doi.org/10.1007/978-981-16-5952-2_33
- Shree, S., Pratap, B., Saroy, R., & Dhal, S. (2021).

Digital payments and consumer experience in India: a survey based empirical study. Journal of Banking and Financial Technology 2021 5:1, 5(1), 1–20. https://doi.org/10.1007/S42786-020-00024-Z

- Sinha, M., Majra, H., Hutchins, J., & Saxena, R. (2019). Mobile payments in India: the privacy factor. International Journal of Bank Marketing. https://doi.org/10.1108/IJBM-05-2017-0099

- Usmonova Durdona Shukhratovna. (2021). Digital banking in the eyes of young professionals | Academic Journal of Digital Economics and Stability. Academic Journal of Digital Economics and Stability, 6, 163–167. http://economics.academicjournal.io/index.php/economics/article/view/91

- Yogesh Chandra, V., & Kapil, B. (2021). Critical Study of Unified Payment Interface (UPI): E-Payment Mode of Digital Revolution | Academic Social Research:(P) ISSN: 2456-2645 , Impact Factor: 4.928 (UGC APPROVED 47715). Academic Social Research, 7(4). http://asr.academicsocialresearch.co.in/index.php/ASR/article/view/582