ACCESS Journal:
Access to Science, Business, Innovation in Digital Economy
2023, 4(1), 130-148, https://doi.org/10.46656/access.2023.4.1(10)

ISSN 2683-1007 (Online)

https://journal.access-bg.org/

PREDICTING ADOPTION OF NEXT GENERATION DIGITAL TECHNOLOGY UTILIZING THE ADOPTION-DIFFUSION MODEL FIT: THE CASE OF MOBILE PAYMENTS INTERFACE IN AN EMERGING ECONOMY

Sanjay Kumar Singh[1], Shivendra Sanjay Singh[2], Vijay Lakshmi Singh[3]

[1] *Indian Institute of Management Lucknow, India*
[2] *Shiv Nadar University, Greater Noida, India*
[3] *Jaipuria Institute of Management Lucknow, India*

e-mails: [1]sanjay@iiml.ac.in, [2]ss668@snu.edu.in, [3]vijaylakshmi.singh@jaipuria.ac.in

Received: 26 December 2022; Accepted: 21 January 2023; Online Published: 27 January 2023

ABSTRACT

The progress and diffusion of next-generation digital technologies are having an enormous effect on industries, innovation, and society. Innovative mobile transaction platforms are becoming the dominant payment system in major emerging economies. This study focuses on estimating the future trend and analyzing the pattern and rate of adoption of the Unified Payments Interface (UPI) in India. UPI is not only decreasing the share of credit and debit cards and other payment modes but also reducing the reliance on cash in the economy. The main aim of this study is to estimate the future trend and analyze the pattern and rate of adoption of UPI in India. Utilizing the S-shaped growth cycle, we discuss the technology diffusion models and find that the Harvey model fits the data better than the Logistic and Gompertz ones. UPI transactions is likely to increase from 45.97 billion in 2021-22 to 643.76 billion in 2030-31. Further, monetary value of UPI transactions is also projected to grow sharply, from Rs.84.18 trillion in 2021-22 to Rs.835.77 trillion in 2030-31. Thus, UPI driven expenditure per person per day is likely to increase from Rs.165 in 2021-22 to Rs.1500 in 2030-31. Results predict that UPI based transactions is likely to increase at manifold levels, both in volume and value terms, having important implications for the economy, especially for payments app developers, internet service providers, the national regulatory agencies, particularly in view of UPI security related risks.

Key Words: Technology diffusion, unified payments interface, growth curve models, mobile payments

JEL Classification: C53, L86, O30, O33

Paper type: Research article

Citation: Singh, S.K.; Singh, S.S.; Singh, V.L. (2023) Predicting Adoption of Next Generation Digital Technology Utilizing the Adoption-Diffusion Model Fit: The Case of Mobile Payments Interface in an Emerging Economy. *Access to science, business, innovation in digital economy,* ACCESS Press, 4(1): 130-148. https://doi.org/10.46656/access.2023.4.1(10)

1. INTRODUCTION AND STUDY BACKGROUND

Technological developments have experienced progressive acceleration in recent decades such that the upsurge of digital economies has become the ‘new normal’ (Ahlstrom et al., 2020). Such changes have evolved from Internet commerce to a mounting range of digital products and services to the current digitalization resulting in the disruption and transformation of traditional sectors and creation of new ones (UNCTAD, 2019). In the last few decades, the world has witnessed surge in digital economies through unprecedented multiplicity and rapid pace of technological innovation diffusions (Cho et al. 2022; Comin &

Hobijn, 2010). Digitalization is reaching every context through the creation of paperless and contactless processes (Shi & Herniman, 2022).

Particularly, the transition in the context of payment fields has been phenomenal in recent decades, with the advent of branchless or internet banking with anytime-anywhere services, followed by mobile banking (Kumar & Yadav, 2022). The automated teller machines, and debit/credit cards are now replaced with near-field communication and contactless mobile payment applications (Glavee-Geo et al., 2019). Instead of the banking sector, originally responsible for designing banking services, including mobile banking, nowadays FinTech companies, example, PayPal and others like Google and Facebook are offering digital payment services on mobiles and tablets (Galande &Borkar, 2021).

Though, adoption of mobile payments is rising, but its future growth and relevance is contingent on the extent of consumer access to new technologies, lifestyle choices and various economic factors (Liébana-Cabanillas & Lara-Rubio, 2017). For example, in the context of developing nations consumers are adopting mobile payments to fulfill their daily need transactions, like utility bills, shopping and personal or individual level fund transfers (Karjaluoto et al., 2021; Shaikh et al., 2022). This is leading to a significant transformation in the socioeconomic conditions of the population at large in non-Western countries (Glavee-Geo et al., 2019; Ramos de Luna et al., 2019).

According to the National Payments Corporation of India (NPCI, 2022), the adoption of digital payments has spiked due to the convenience they provide, among other factors. In the case of India, one of the largest developing economies, the country is experiencing the digital payment revolution led by the Unified Payments Interface (UPI) platform. UPI, an instant real time mobile phone based payment system regulated by the Reserve Bank of India (RBI) and developed by the National Payments Corporation of India (NPCI), is proving to be one of the best financial innovation post-independence in India. Looking at the pace of user adoption, UPI platform is in the process of almost replacing the cash economy. UPI allows immediate transaction from one bank account to another through a smartphone application (such as Paytm, PhonePe, Google Pay, BHIM UPI, etc.); transaction can take place through scanning of Quick Response (QR) codes, registered phone number, or even through the Indian Financial System Code (IFSC) details. UPI applications can also be used to pay home bills, transit charges, and also to avail financial services like payment of loans and credit card bills and almost all required shopping and payments. Unlike credit cards, UPI payments are free of cost; there is no extra charge for doing a UPI payment. One can transfer just one rupee without paying any transaction fee (NPCI, 2022).

In fact, the latest data captures the explosion in adoption of UPI platform in India. Across the country, almost all types of end users, such as merchants, service providers, small companies, traders, vendors as well as individual customers have already made UPI a part of their daily life. According to the latest data compiled by the NPCI, number of UPI transactions and monetary value of the same have doubled during the last fiscal year; number of transactions have increased from 22.33 billion in 2020-21 to 45.97 billion in 2021-22 while monetary value of transactions have increased from Rupee 41.04 trillion in 2020-21 to Rs. 84.18

trillion in 2021-22 (refer, Figure 1). When UPI platform began its operation in July 2016, there were only 21 banks on the board. The number of banks that are currently working on UPI has gone up to 323 from 220 in April 2021 and 153 in April 2020 (NPCI, 2022).

However, an effective management and regulation of UPI platform requires an understanding of the evolution of the market. Factors such as market potential, the timing and speed of adoption are critically significant for digital payment apps using UPI platform for their capacity building and business growth. Understanding the progression of UPI market and its prospective future trend is important for industry regulators as well as policy makers. The adoption of mobile phones, mobile banking, and digital payments has been widely investigated in developed countries (see for example, Bewley & Fiebig, 1988; Carrillo & Gonzalez, 2002; Jiang et al. 2021; Lashitew et al. 2019; Macvaugh & Schiavone, 2010; Martino, 2003; Meade & Islam, 1995; Panik, 2014). However, there is a dearth of such studies in the context of developing nations (such as, Asongu et al. 2020; Gao & Owolabi, 2008; Ramdhony & Munient, 2013; Zhu et al. 2021) and very few in India, one of the largest emerging economies of the world (e.g., Choudrie et al. 2018; Jha & Saha, 2020; Singh, 2008; Sivathanu, 2019). These existing few studies have majorly explored the internet banking and mobile banking adoption (e.g., Choudrie et al. 2018; Jha & Saha, 2020), and none examining the diffusion of latest technology innovation of UPI payment transactions through mobiles. Therefore, it is imperative to estimate and understand the dynamics of the new age technological diffusion extent and levels in order to plan and formalize timely policies and guide industrial and business growth, especially in the context of India, being one of the largest emerging economies of the world and a free market with major global footprints in business. Scholars have already suggested to undertake further studies on adoption of mobile based payments, in view of its extremely rapid pace of expansion and rising trend (Kumar & Yadav, 2022; Shaikh et al., 2022).

Further, the scholarly literature on innovation management has particularly focused on the adoption of new age digital technologies (van Lente & Arie, 2017). Technology adoption or diffusion models estimate the process by which an innovation is diffused and how technologies are adopted at end user level (Rogers et al., 2014). For more than a half century, innovation research and practice has been dominated by diffusion *S*-curve models (Shi & Herniman, 2022). This growth curve model has been widely utilized for predicting technological change rates, detecting probable technological ruptures, and in determining the limits of particular technology adoption (Nieto et al, 1998). In the particular context of studies on mobile payments adoption, earlier scholars have utilized various methodological models, but majorly the technology acceptance models and multivariate analysis techniques, example, the structural equation models dominate the existing literature, which mostly comprised of micro-level or organization specific studies. It has been recommended that application of other statistical techniques, as well as macro-level studies could reveal various other factors and dynamics in understanding mobile based payments, especially from the country's economy perspectives (Kumar & Yadav, 2022) Specifically, the *S*-curves or technology adoption curves has been used to describe, estimate, and predict the growth, maturity, diffusion, and transformation of innovations (Cho et al., 2022). However, as already discussed earlier, not many studies exist using such tools, and especially in developing countries, which is currently the seat of such pacing growth, and almost none in the specific case of UPI payments in India, an emerging global market leader.

Hence, the objective of this study is to estimate the future trend and analyze the pattern and rate of adoption of UPI platform in India. The paper uses *S*-shaped growth curve functions to model the development in UPI based transactions and monetary value of the same. National level data from July 2016 to March 2022 are used for the purpose of estimation of the models. We predict the adoption of UPI in India to inform the larger discussion of managing the UPI platform as well as to assist analysts concerned about assessing the impact of public policies and regulation in the evolution of the banking and financial sectors as well as impact of innovative technology applications. The remaining part of this paper is organized into the following sections- Section 2 presents the adoption-diffusion model, Section 3 details the model estimation, result, and its analysis, and finally Section 4 discusses the implications, concluding remarks as well as limitations of the study and future research.

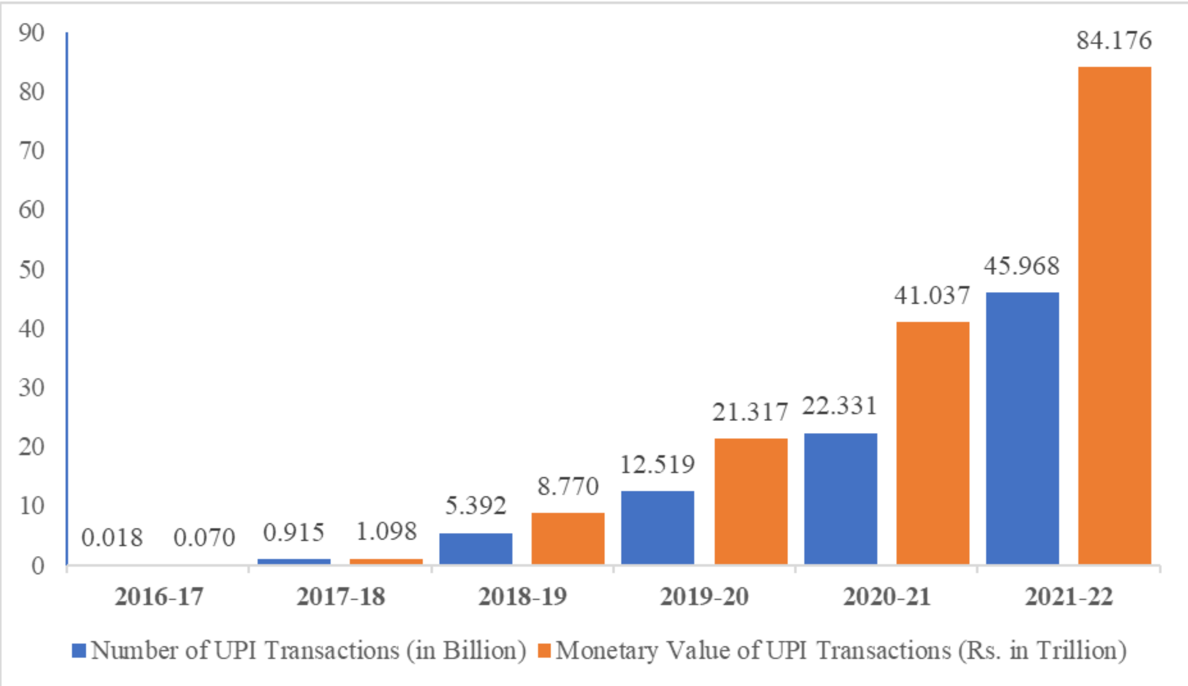

Fig. 1. Adoption of UPI platform in India

Source: Authors' calculations

2. METHODS - THE MODEL

In the traditional technology life cycle or *S*-curve model, 'the early phases of innovation are marked by a rapid rise in expectations of the innovation, toward the peak of inflated expectations and then a rapid decline through the trough of disillusionment, leading to early adoptions and rapid market growth' (Shi & Herniman, 2022). The *S*-curve growth models have been extensively applied for forecasting, estimation, and

ISSN 2683-1007 (Online)
2023, 4(1), 130-148, https://doi.org/10.46656/access.2023.4.1(10)
https://journal.access-bg.org/

transformation of technologies and innovations (Christensen, 2014; Kucharavy & Roland, 2011; Rogers, 2014).

The Logistic and Gompertz models are attractive and popular in situations where there is thought to be a saturation level to a time series. A large number of researchers have used these models either in its simplest form (Botelho & Pinto, 2003; Franses, 1994; Jiang et al. 2021) or in a modified form (Al-Jabri & Sohail, 2012; Chow, 1967; Hu et al. 2019), in analyzing various technological changes (Asongu et al. 2020; Choudrie et al. 2018). These models have also been successful in forecasting adoption of mobile phones, mobile banking, and digital payment (Asongu et al. 2020; Jha and Saha, 2020; Sivathanu, 2019; Zhu et al. 2021).

The Logistic and Gompertz models use a Fibonacci search technique to evaluate the saturation level; the saturation level requires to be calculated before the parameters of the models are estimated (Meade & Islam, 1998; Mohamed & Bodger, 2005). Moreover, there is a possibility of underestimation or overestimation of the final ceiling (Asongu et al. 2020; Harvey 1984, 1990; Mohamed & Bodger, 2005). This is mainly due to the constraints imposed by the saturation level of the Logistic and Gompertz models. However, these models can be transformed in a manner so that they do not require estimation of the saturation level (Harvey, 1990). Nevertheless, the models approach a saturation level with time.

2.1. Logistic model

UPI adoption, $U(t)$, can be represented by the Logistic function as,

$$U(t) = \frac{\alpha}{1+\beta e^{\gamma t}} \tag{1}$$

where α is the saturation level, β and γ are parameters to be estimated, and t is the time in years.

To transform the model in a linear form, equation (1) is differentiated with respect to t and natural logarithms taken on both sides, the following equation is obtained.

$$dU(t)/dt = [U(t)]^2(-\beta\gamma/\alpha)e^{\gamma t}$$

$$\Rightarrow ln(dU(t)/dt) = 2lnU(t) + ln(-\beta\gamma/\alpha) + \gamma t$$

$$\Rightarrow lnu(t) = \delta + 2lnU(t) + \gamma t \tag{2}$$

where $\delta = ln(-\beta\gamma/\alpha)$ and $u(t) = U_t - U_{t-1}$.

Using equation (2), the proposed Logistic model is,

$$lnu(t) = \delta + 2lnU(t) + \gamma t + \varepsilon_t \tag{3}$$

where ε_t is a disturbance term and $t = 2, 3, \ldots, T$.

Equation (3) is rearranged to give:

$$ln(u_t/U_t^2) = \delta + \gamma t + \varepsilon_t \tag{4}$$

where δ and γ are parameters to be estimated using ordinary least squares (OLS) and ε_t is a disturbance term with zero mean and constant variance.

2.2. Gompertz model

Gompertz function is of the form,

$$U(t) = \alpha e^{\beta e^{\gamma t}} \tag{5}$$

where α is the saturation level, β and γ are parameters to be estimated, and t is the time in years.

To transform the model in a linear form, equation (5) is differentiated with respect to t and natural logarithms taken on both sides, the following equation is obtained.

$dU(t)/dt = [U(t)](\alpha\beta\gamma)e^{\gamma t}$

$\Rightarrow ln(dU(t)/dt) = lnU(t) + ln(\alpha\beta\gamma) + \gamma t$

$$\Rightarrow lnu(t) = \delta + lnU(t) + \gamma t \tag{6}$$

where $\delta = ln(\alpha\beta\gamma)$ and $u(t) = U_t - U_{t-1}$.

Using equation (6), the proposed Gompertz model is,

$$lnu(t) = \delta + lnU(t) + \gamma t + \varepsilon_t \tag{7}$$

where ε_t is a disturbance term and $t = 2, 3, \ldots, T$.

Equation (7) is rearranged to give:

$$ln(u_t/U_t) = \delta + \gamma t + \varepsilon_t \tag{8}$$

where δ and γ are parameters to be estimated using OLS and ε_t is a disturbance term with zero mean and constant variance.

2.3. Harvey model

Harvey model (Harvey, 1984) is based on the general modified exponential function which can be written as,

$$U(t) = \alpha(1 + \beta e^{\gamma t})^{\eta} \tag{9}$$

where all the variables have their previous meaning and the value of η determines the form of the function $U(t)$. For example, when η = -1, $U(t)$ is Logistic function and when η = 1, it is a simple modified exponential function.

To transform the model in a linear form, equation (9) is differentiated with respect to t and natural logarithms taken on both sides, the following equation is obtained.

ACCESS Journal:
Access to Science, Business, Innovation in Digital Economy
2023, 4(1), 130-148, https://doi.org/10.46656/access.2023.4.1(10)
ISSN 2683-1007 (Online)
https://journal.access-bg.org/

$dU(t)/dt = \alpha\beta\gamma\eta(1+\beta e^{\gamma t})^{\eta-1}e^{\gamma t}$

$\Rightarrow dU(t)/dt = [\alpha^{1/\eta}\beta\gamma\eta][U(t)^{(\eta-1)/\eta}]e^{\gamma t}$

$\Rightarrow ln(dU(t)/dt) = ln(\alpha^{1/\eta}\beta\gamma\eta) + ((\eta-1)/\eta)lnU(t) + \gamma t$

$$\Rightarrow lnu(t) = \delta + \rho lnU(t) + \gamma t \tag{10}$$

where $\delta = ln(\alpha^{1/\eta}\beta\gamma\eta)$, $\rho = (\eta-1)/\eta$, and $u(t) = U_t - U_{t-1}$.

Using equation (10), the proposed Harvey model is,

$$lnu_t = \delta + \rho lnU_t + \gamma t + \varepsilon_t \tag{11}$$

where ε_t is a disturbance term and $t = 2, 3, \ldots, T$.

where δ, ρ and γ are parameters to be estimated using OLS and ε_t is a disturbance term with zero mean and constant variance.

The mean absolute percentage error (MAPE) and the Durbin-Watson (DW) statistic can be used to assess the performance of different models (Asongu et al. 2020; Choudrie et al. 2018; Franses, 2002; Harvey, 1984; Mansfield, 1961; Meade & Islam, 1995; Singh, 2008). The MAPE is commonly used in quantitative forecasting methods because it produces a measure of relative overall fit and compares the forecasting accuracy of the models. The DW statistic tests whether the residuals of the fitted model are independent. In other words, the DW statistic is a measure of autocorrelation. The null hypothesis that there is no correlation between the successive residuals is evaluated by $DW = \frac{\sum_{t=2}^{T}(\varepsilon_t - \varepsilon_{t-1})^2}{\sum_{t=1}^{T}\varepsilon_t{}^2}$, where ε_t is the residual corresponding to the t^{th} observation and ε_{t-1} is the residual of the preceding observation. The DW statistic will always have a value ranging between 0 and 4. A value of 2 indicates that there is no autocorrelation detected in the sample. Values from 0 to less than 2 points to positive autocorrelation and values from 2 to 4 means negative autocorrelation. As a rule of thumb, the DW statistic between 1.5 and 2.5 is inferred to indicate independence of observations.

F-test can be used to test the validity of restriction on coefficients. For example, whether $\rho = 0$ is valid or not can be tested using F-test. The F-test statistic is calculated as $\frac{(R_{ur}^2 - R_r^2)/r}{(1-R_{ur}^2)/(N-k)}$ where R_{ur}^2 is the R^2 value obtained from the unrestricted regression model, R_r^2 is the R^2 value obtained from the restricted regression model, r is the number of restrictions imposed, N is the number of observations and k is the number of parameters in the unrestricted regression model. This statistic follows F-distribution with r, N-k degrees of freedom. If calculated F value is greater than the tabulated one, we reject the null hypothesis of restriction on coefficients. Therefore, the MAPE, DW and F-test can be used to find out the most appropriate model to analyze the adoption of UPI in India.

3. RESULTS - MODEL ESTIMATION AND ANALYSIS

3.1. Number of UPI transactions

The Logistic model (4), Gompertz model (8), and Harvey model (11) are estimated using the data of number of UPI transactions in India from 2016-17 to 2021-22 by OLS method. Monthly transaction data, from July 2016 to March 2022, is taken from the NPCI. Equations (12), (13), and (14) present regression results for the Logistic, Gompertz, and Harvey models, respectively. According to the R^2 values, models fit the data very well. Estimated parameters have the expected signs and most are highly significant. The residuals of all the models are well behaved with a DW statistic ranging from 1.484 for Gompertz model to 2.329 for Harvey model. We also compare the estimated values with the actual values over the sample period for all the models. The MAPE is the lowest, 1.157, for the Harvey model and highest for the Gompertz model. According to both R^2 and MAPE, Harvey model fits the data better than the Logistic and Gompertz models. For Harvey model, we also test the null hypotheses of $\rho=0$ and $\gamma=0$. According to F-test, the null hypotheses are rejected at 5% level of significance. Therefore, to project the number of UPI transactions in India up to the year 2030-31, we use the estimated Harvey model as shown in equation (14).

$$\text{Logistic: } \ln(u_t/U_t^2) = -5.098 - 1.118t;\ R^2 = 0.945,\ MAPE = 4.032,\ DW = 1.484 \qquad (12)$$

$$\text{Gompertz: } \ln(u_t/U_t) = 0.319 - 0.193t;\ R^2 = 0.821,\ MAPE = 68.127,\ DW = 1.991 \qquad (13)$$

$$\text{Harvey: } \ln u_t = 0.969 + 0.880 \ln U_t - 0.082t;\ R^2 = 0.987,\ MAPE = 1.157,\ DW = 2.329 \qquad (14)$$

Figure 2 presents the number of UPI transactions in India using the Harvey model. Number of UPI transactions in India is projected to grow rapidly, from around 46 billion in 2021-22 to 644 billion in 2030-31, an increase of 14 times in a span of just 9 years. Number of UPI transaction per person per day is expected to surpass the mark of 1 in 2029-30. This is because projected number of transactions in 2029-30 is 544 billion whereas Indian population is likely to be slightly less than 1.5 billion by that time. As far as growth in number of transactions is concerned, number of transactions grew at the rate of more than 100% from FY21 (i.e., fiscal year 2020-21) to FY22. It is likely to grow at the rate of around 63% from FY22 to FY23 and 51% from FY23 to FY24 (Figure 3). Growth in number of transactions will decelerate further; it is projected that the growth will be slightly more than 18% from FY30 to FY31. Although we do not present the predicted values till 2035-36, number of UPI transactions is predicted to increase in double digit till that time, 10.5% from FY35 to FY36. That's why, number of transactions is predicted to surpass the mark of 1 trillion in FY35. According to the National Commission on Population (NCP) under the Ministry of Health and Family Welfare, Government of India, Indian population in 2035-36 will be around 1.52

billion (NCP, 2022). Therefore, number of UPI transaction per person per day is likely to be very close to 2, 1.95 to be precise, in 2035-36.

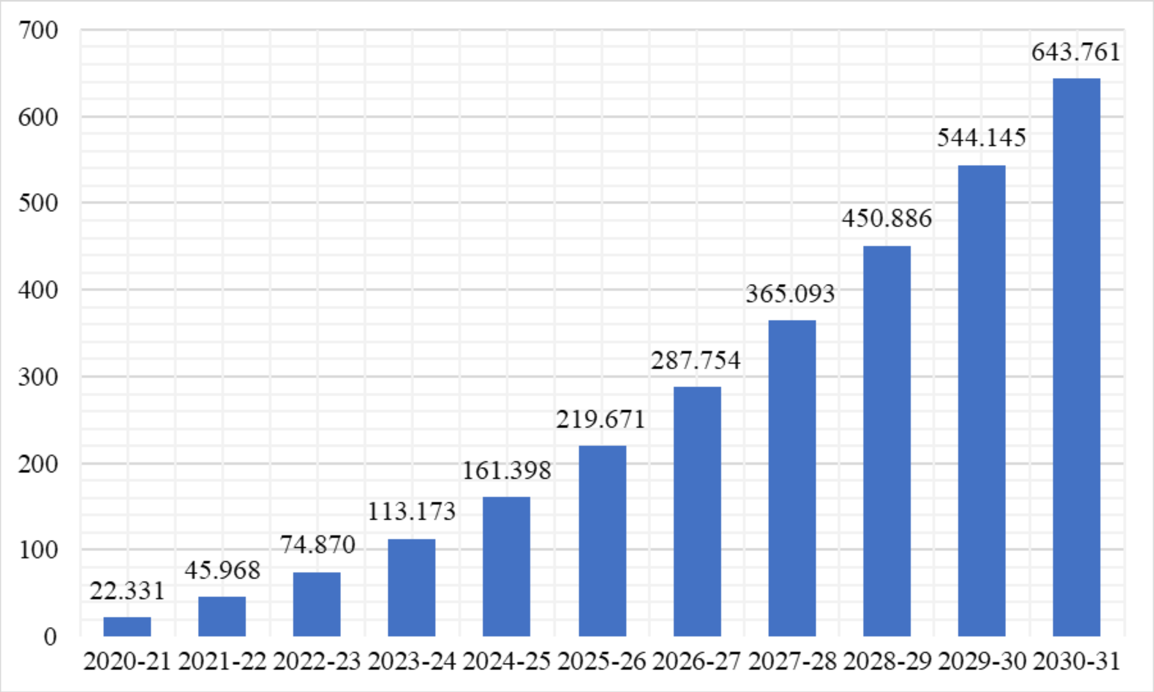

Fig. 2. Projection of number of UPI transactions in India using the Harvey model (in billion)

Source: Authors' calculations

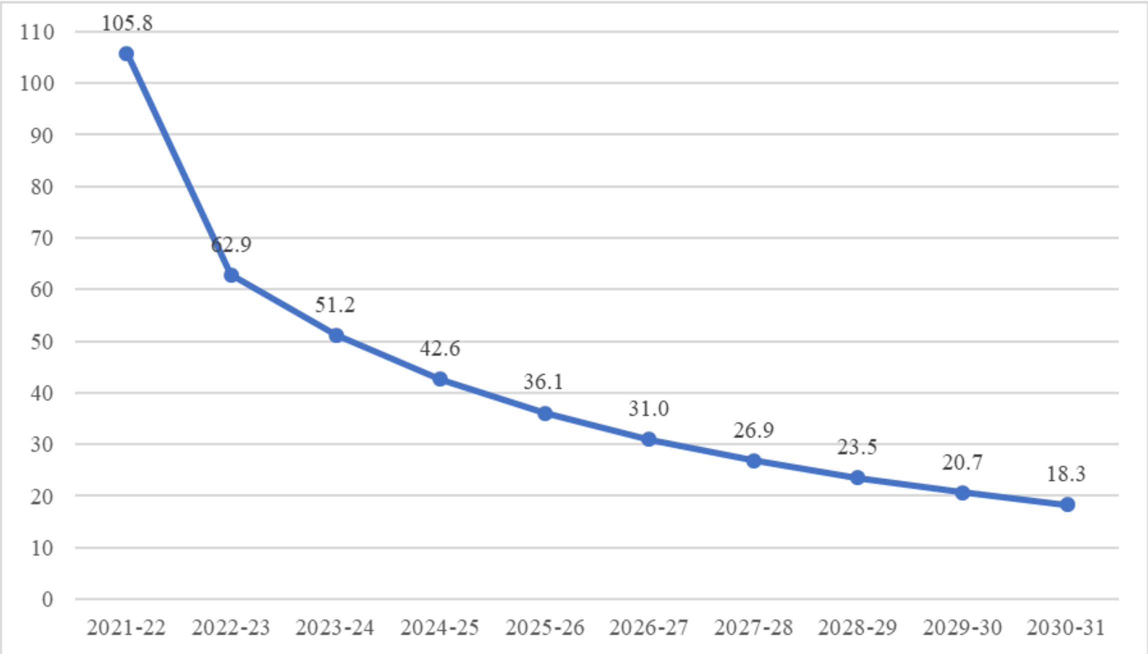

Fig. 3. Projected annual growth rate with respect to previous period in number of UPI transactions in India using the Harvey model (in percentage)

Source: Authors' calculations

3.2. Monetary value of UPI transactions

We also estimate the Logistic, Gompertz, and Harvey models using the monetary value of UPI transactions. Estimated equations (15), (16), and (17) present the regression results for the Logistic, Gompertz, and Harvey models, respectively. According to the R^2 values, models fit the data very well. Estimated parameters have the expected signs and most are highly significant. The residuals of all the models are well behaved with a DW statistic ranging from 1.505 for Logistic model to 2.243 for Gompertz model. We also compare the predicted values with the actual values over the sample period for all the models. The MAPE is the lowest, 0.980, for the Harvey model and highest for the Gompertz model. According to both R^2 and MAPE, Harvey model fits the data better than the Logistic and Gompertz models. For Harvey model, we also test the null hypotheses of $\rho=0$ and $\gamma=0$. According to F-test, the null hypotheses are rejected at 5% level of significance. Therefore, to project the monetary value of UPI transactions in India up to the year 2030-31, we use the estimated Harvey model as shown in equation (17).

$$\text{Logistic: } ln(u_t/U_t^2) = -5.218 - 1.207t;\ R^2 = 0.943,\ MAPE = 4.233,\ DW = 1.505 \quad (15)$$

$$\text{Gompertz: } ln(u_t/U_t) = 0.296 - 0.181t;\ R^2 = 0.859,\ MAPE = 27.725,\ DW = 2.243 \quad (16)$$

$$\text{Harvey: } lnu_t = 0.422 + 0.977lnU_t - 0.157t;\ R^2 = 0.993,\ MAPE = 0.980,\ DW = 2.344 \quad (17)$$

Figure 4 presents the monetary value of UPI transactions in India using the Harvey model. Monetary value of UPI transactions in India is projected to grow sharply, from around Rs. 84 trillion in 2021-22 to nearly Rs. 836 trillion in 2030-31, an increase of almost 10 times in a span of just 9 years. Consequently, UPI transaction value, which was 36% of nominal GDP of India in 2021-22, is likely to grow to 95% of nominal GDP of the country by 2030-31 (refer Figure 5 for projected values of nominal GDP; projection is based on the trend in nominal GDP, published by the Central Statistics Office, Ministry of Statistics and Programme Implementation, Government of India, New Delhi, during the last ten years (NAD, 2022)). On an average, every Indian spent Rs. 165 per day using UPI in 2021-22; this expenditure will increase more than 9-fold in just 9 years. UPI driven expenditure in India in 2030-31 is likely to cross the mark of Rs. 1500 per person per day. This is because monetary value of total transactions in 2030-31 is projected to be Rs. 835.772 trillion whereas Indian population is likely to be slightly more than 1.5 billion by that time. As far as growth in transaction value is concerned, it grew at the rate of more than 100% from FY21 to FY22. Monetary value of UPI transactions is likely to grow at the rate of around 63% from FY22 to FY23 and 49% from FY23 to FY24 (Figure 6). Double digit growth will continue till 2030-31. Although we do not present the projected values till 2035-36, monetary value of UPI transactions is projected to increase in single digit till that time, 9.9% from FY31 to FY32 to 5.0% from FY35 to FY36. Nevertheless, UPI driven transactions will cross the mark of Rs. 1 quadrillion in FY34, just one year before when the number of transactions will cross the mark of 1 trillion in FY35.

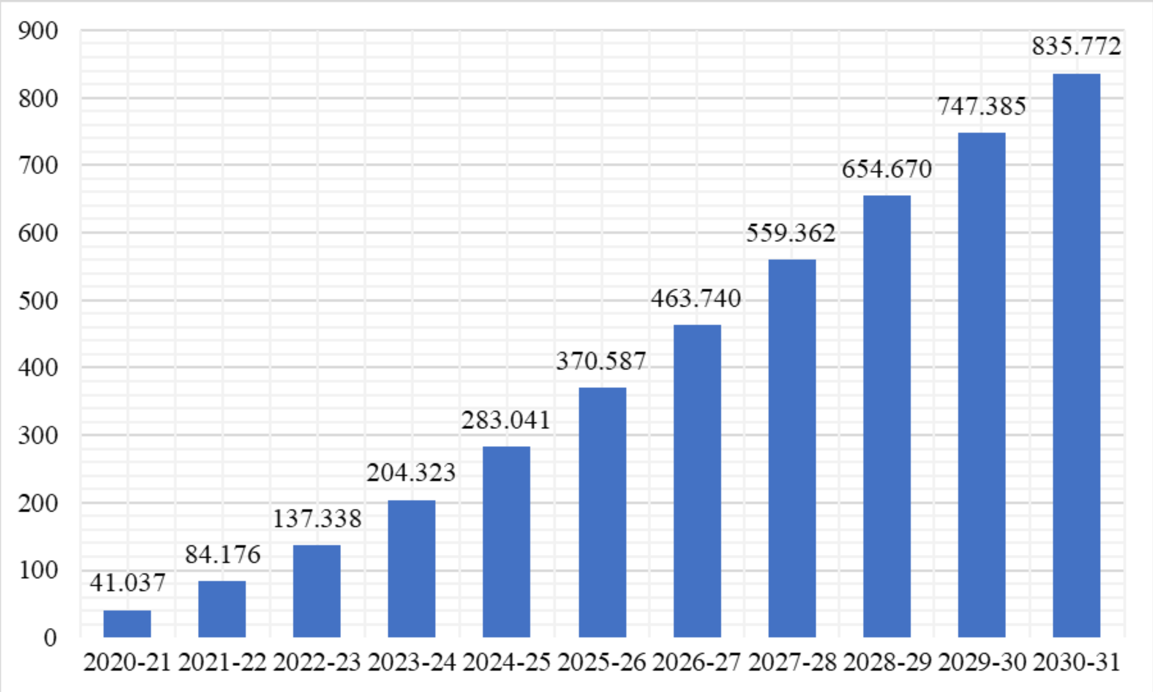

Fig. 4. Projection of monetary value of UPI transactions in India using the Harvey model (Rs. in trillion)

Source: Authors' calculations

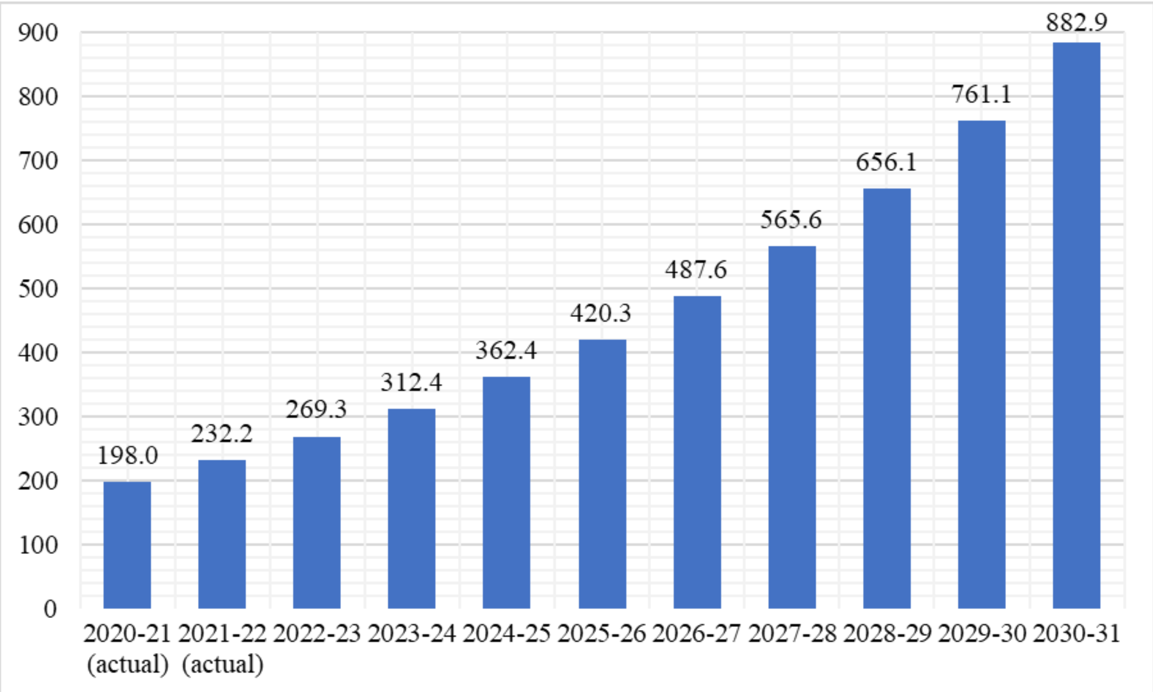

Fig. 5. Projected value of nominal GDP of India. (Rs. in trillion)

Source: Authors' calculations

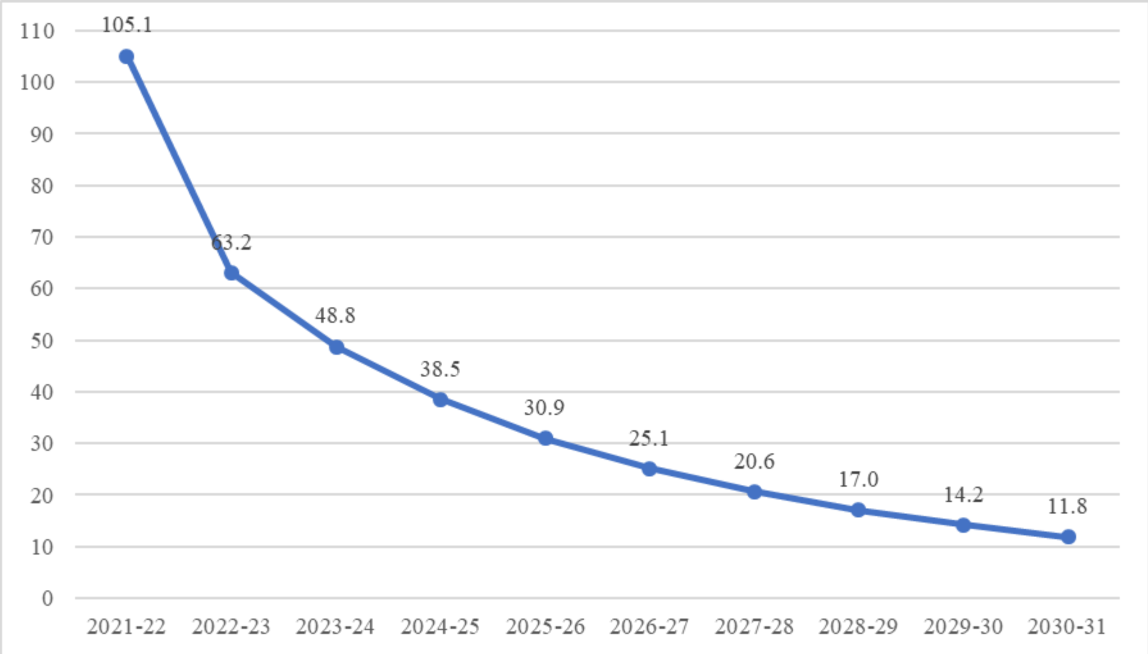

Fig. 6. Projected annual growth rate with respect to previous period in monetary value of UPI transactions in India using the Harvey model (in percentage)
Source: Authors' calculations

Since number of UPI transactions is projected to increase at higher rate than the monetary value of the same, average value per transaction is predicted to fall from Rs. 1831 in 2021-22 to Rs. 1298 in 2030-31. Average value per transaction is likely to be more than Rs. 1000 only till 2034-35; it will fall below Rs. 1000 from 2035-36 (Rs. 991) onwards. This is because UPI has now emerged as the most preferred payment option among almost all types of end users, with a peer-to-merchant (P2M) market share of 56% in terms of the number of transactions and 41% in monetary value of the same (Worldline, 2022). Out of total UPI transactions, 62% are peer-to-peer (P2P) transactions while 38% are P2M ones; average value of P2M transaction, Rs. 786, is far less than that of P2P ones. Given that UPI is a very convenient and easy to understand mode of payment, it has become a preferred choice for roadside vendors to stores in a shopping mall. According to NPCI, 50% of P2M transactions are of less than Rs. 200, showing that people prefer to use UPI for small amount transactions. As more and more people would start using UPI instead of carrying notes and coins for making transactions, it is expected that the average value per UPI transaction would fall further. Nevertheless, it is pertinent to note that UPI P2M transactions has significantly reduced the share of card and other payment modes; in 2021, credit cards' volume and value stood at 2.15 billion and Rs 8.88 trillion respectively, while debit card transactions' volume and value stood at 4.12 billion and Rs 7.42 trillion respectively. In January 2022, the share of credit cards in retail digital payments stood under 2%, whereas that of UPI was a whopping 18%. It used to be below 9% in 2020. It is amply clear that UPI is not only pushing credit cards out of the arena but also replacing cash in payments ecosystem. It is already the single largest retail payment platform, in terms of volume of transactions, in the country (EcoSurvey, 2022).

ACCESS Journal:
Access to Science, Business, Innovation in Digital Economy
2023, 4(1), 130-148, https://doi.org/10.46656/access.2023.4.1(10)
ISSN 2683-1007 (Online)
https://journal.access-bg.org/

4. DISCUSSION AND CONCLUSIONS

This study analyzes the adoption of UPI for monetary transactions in India and contributes to the scholarship and practice concerning the management of innovative technologies, specifically the UPI platform, and also informs analysts and data scientists involved in the assessment of the impact of public policies and regulation in the evolution of the fin-tech sector. The paper uses *S*-shaped growth curve models, Logistic, Gompertz, and Harvey ones, to model the development in UPI based transactions and monetary value of the same.

As per best fit estimated Harvey model, the number of UPI transactions in India is likely to increase 14-fold in a span of 9 years from now. Consequently, number of UPI transaction per person per day is likely to cross the mark of 1 by 2029-30. Monetary value of UPI transactions is also projected to grow sharply, consequently, UPI transaction value, which was 36% of nominal GDP of India in 2021-22, is likely to grow to 95% of nominal GDP of the country by 2030-31. Thus, UPI driven expenditure per person per day is likely to rise to more than 9-fold increase in just 9 years. Since number of UPI transactions is projected to increase at higher rate than the monetary value of the same, average value per transaction is predicted to fall from Rs. 1831 in 2021-22 to Rs. 1298 in 2030-31. The projected pace of growth in UPI transactions has significant implications for payments app developers, internet service providers, NPCI, and the UPI regulator - RBI. NPCI and RBI will have to pay special attention on UPI security risks; users, particularly who don’t have a good understanding of technology, need to be protected from fraudsters in terms of privacy breach and security measures.

UPI is set to become the main mode of payment both for P2P and P2M transactions. It is not only decreasing the share of credit and debit cards and other payment modes but also reducing the reliance on cash for various kinds of transactions. As per the latest data, number of UPI transactions and monetary value of the same have doubled during the last fiscal year. There are many factors leading to such a massive adoption of UPI payments in India. Important ones are as follows:

a. tremendous growth in number of smartphone users - according to the Telecom Regulatory Authority of India, India has 750 million smartphone users out of 1.2 billion mobile subscribers in 2021 (TRAI, 2022). Given the trend, number of smartphone users in the country is likely to be 1 billion by 2026 as 5G services are rolled out. As internet enabled phone users are increasing across all sections of society and regions, adoption of UPI is increasing rapidly since consumers make the UPI payments with the help of smartphones.

b. convenience - the process of creating an UPI ID is very simple; consumers can create their Virtual Payment Address (VPA) through any UPI Payment Service Provider (PSP) app like Paytm which has a user-friendly interface. Although consumers’ bank account is linked to their VPA, they do not require their bank details while making a transaction. This makes the process faster and less complicated for the consumers.

c. cross operability - consumers can use UPI to make transaction from one PSP (say, Paytm) to another one (say, Google Pay); so, it is not obligatory for UPI users to install all PSPs on their smartphones. The security that is set up by the user while creating an UPI ID is also uniform across all the PSPs.
d. adoption by merchants - large number of merchants in India have started to use the UPI to receive the payments. This is an important factor contributing to UPI's rapid growth, especially when we consider transactions of day-to-day expenses. Since UPI does not put any transaction fee on the merchants, they do not hesitate to use it. In fact, both P2M as well as P2P transactions through UPI are free of charges. Using UPI for the payments eliminates the problem of carrying cash for customers as well as merchants. For small merchants, this resolves the problem of keeping cash for returning loose change for small amount payments.
e. better than mobile wallets - mobile wallets do not pay interest for storing money whereas, when using UPI, funds stay in the bank account itself, which pays interest accordingly.

There is no doubt that the UPI is a remarkable financial innovation. UPI will help India to move towards a cashless economy. It will not only increase transaction efficiency but also mitigate corruption arising from cash transactions. However, UPI will face challenges as it continues to grow. Major challenges are likely to be as follows:

a. internet bandwidth - low internet bandwidth can be a problem for UPI users as UPI based transaction is heavily dependent on internet. This can be critical when transaction has to be made urgently. In areas, especially rural areas, where it is difficult to access internet, UPI can very much be of no use as transactions cannot take place.
b. delayed and failed transactions - consumers sometime face the problem of delayed or failed transactions. This usually happens either due to slow speed of internet or when the respective bank's server faces some problem. When the internet speed is slow, the delay may be short, although that can also become very problematic in case the PSP application neither accepts nor declines the transaction, which leaves the user unsure of whether the amount has been deducted or not, but in the case when a bank's server is unable to respond, it may take up to 48 hours to resolve the issue, which may be problematic specially for consumers solely dependent on UPI for daily payments.
c. daily transaction limit - UPI has a daily transaction limit of Rs. 100,000/- as of now. One cannot make use of UPI for transactions after exceeding the daily limit. This may discourage people from using UPI at a larger scale in the coming future, unless the current ceiling is revised.
d. security issues - as stated earlier, UPI being so convenient to use has indeed led to significant increase in the user base of the payment system, but with that, security risks have also increased. A platform with such a growing user base becomes an opportunity for fraudsters and users, particularly who don't have a very strong understanding of technology, can become a victim. Some of the most common scams can be phishing, remote screen-monitoring, fraud phone calls, using fake UPI handles, and using unverified links to retrieve sensitive details of users.

Most of these issues are very much expected when it comes to a rapidly growing online payments platform. However, solutions for these problems can be brought up in the future. Advancement in technology and updates in UPI as a platform can very much curb fraudulent cases. Nevertheless, central or government regulatory agencies such as NPCI and RBI will have to pay special attention on security issues so that customers can continue to have confidence in mobile based UPI transactions.

Further, this research is not without limitations. Since, the study relates to the specific prediction of innovation technology usage, i.e., of mobile app based UPI mode of payment, in terms of adoption behavior of consumers at the macro level, future studies can look into the adoption behavior and estimation of other innovative technologies, such as the alternate platform of mobile/smartphone banking or in fact the new in-app embedded payment features (e.g., in WhatsApp) or rather compare between various UPI payment transaction options. Moreover, we use yearly data for prediction, but future studies can also consider utilizing monthly data for adoption estimation that can offer insights into seasonality of utilization behavior at the aggregate consumer level. In terms of the methodology adopted, future studies can instead utilize alternate growth models, e.g., the Bass model (Turk & Trkman, 2012), for estimating new generation technology adoption, which might offer a more comprehensive output on account of including more number of factors for analysis. Further studies can also attempt to analyze a more robust model of prediction by including various other relevant factors for adoption of innovative technology, such as, literacy level of the population, income level of users, extent of smart phone usage etc. Studies from an interdisciplinary perspective, e.g., consumer behavior, and those applying other methods of research inquiry, e.g., the survey method, can also contribute by corroborating the results of this study in terms of revealing the adoption behavioral patterns of UPI payment transactions and other new age innovative technologies.

To conclude, this study utilizing the *S*-shaped growth curve models for forecasting, finds that the Harvey model fits the data better than the Gompertz and Logistic models for estimation of the adoption of new generation technology. Further, this study deals with the analysis of pattern and rate of adoption of mobile UPI payment as well as estimation of its future trend, both on the basis of number and value of payment transactions. This paper also outlines and discusses the implications of the estimated growth trends for the mobile app payment economy. The study contributes to the existing scholarly literature on the management of technology and innovation by suggesting *S* curve growth model to best fit the purpose of estimating the adoption of new age technology, specifically mobile UPI transactions, in the context of one of the largest emerging economies.

Author Contributions:

For research articles with several authors, the following statements should be used Conceptualization, Singh, S.K. and Singh, S.S.; methodology, Singh, S.K.; validation, Singh, S.K., Singh, S.S. and Singh, V.L.; formal analysis, Singh, S.K.; data curation, Singh, S.S.; writing - original draft preparation, Singh, S.K., Singh, V.L. and Singh, S.S.; writing - review and editing, Singh, S.K. and Singh, V.L.; visualization, Singh, S.S. and Singh, V.L. All authors have read and agreed to the published version of the manuscript.”

Institutional Review Board Statement: not applicable

Informed Consent Statement: not applicable

Data Availability Statement: not applicable (Data used are in public domain and source of the same is given in the References)

Acknowledgement

We would like to thank Dr. Sanjeet Singh (Professor, Indian Institute of Management Lucknow) for his helpful comments and valuable suggestions which considerably improved the exposition of this work.

Conflict of interests

The authors declare no conflict of interest.

References

Ahlstrom, D., Arregle, J. L., Hitt, M. A., Qian, G., Ma, X., Faems, D. (2020). Managing technological, sociopolitical, and institutional change in the new normal. *Journal of Management Studies*, 57(3), 411-437.

Al-Jabri, I. M., Sohail, M. S. (2012). Mobile banking adoption: Application of diffusion of innovation theory. *Journal of Electronic Commerce Research*, 13(4), 379-391.

Asongu, S. A., Biekpe, N., Cassimon, D. (2020). Understanding the greater diffusion of mobile money innovations in Africa. *Telecommunications Policy*, 44(8), Article 102000.

Asongu, S. A., Biekpe, N., Cassimon, D. (2021). On the diffusion of mobile phone innovations for financial inclusion. *Technology in Society*, *65*, Article 101542.

Bewley R., Fiebig D. (1988). Flexible logistic growth model with applications in telecommunications. *International Journal of Forecasting*, 4(2), 177-192.

Botelho A., Pinto L. C. (2004). The diffusion of cellular phones in Portugal. *Telecommunications Policy*, 28(5-6), 427-437.

Carrillo, M., González, J. M. (2002). A new approach to modelling sigmoidal curves. *Technological Forecasting and Social Change*, 69(3), 233-241.

Cho, Jaehan., DeStefano, Timothy., Kim, Hanhin., Kim, Inchul. & Paik, Jin Hyun. (2022). What's driving the diffusion of next-generation digital technologies? *Technovation*, Article 102477.

Choudrie, J., Junior, C. O., McKenna, B., Richter, S. (2018). Understanding and conceptualizing the adoption, use and diffusion of mobile banking in older adults: A research agenda and conceptual framework. *Journal of Business Research*, 88, 449-465.

Chow G. C. (1967). Technological change and the demand for computers. *American Economic Review*, 57(5), 1117-1130.

Christensen, Clayton M. (1992). Exploring the limits of the technology S-curve. Part I: component technologies. *Production and Operations Management*, 1(4), 334-357.

Comin, D., Hobijn, B. (2010). An exploration of technology diffusion. *American Economic Review*, 100(5), 2031-59.

EcoSurvey. *Economic Survey 2021-22* (2022). Ministry of Finance, Government of India, New Delhi. Retrieved from: https://www.indiabudget.gov.in/economicsurvey/doc/echapter.pdf (2022). (accessed on 2 November 2022)

Franses, P. H. (1994). A method to select between Gompertz and logistic trend curves. *Technological Forecasting and Social Change*, 46(1), 45-49.

Franses, Philip Hans. (2002). Testing for residual autocorrelation in growth curve models. *Technological Forecasting and Social Change*, 69(2), 195-204.

Galande, M. A., Borkar, D. S. (2021). Digital payment: The canvas of Indian banking financial system. European Journal of Molecular & Clinical Medicine, 7(8), 5868–5871.

Gao, P., Owolabi, O. (2008). Consumer adoption of internet banking in Nigeria. *International Journal of Electronic Finance*, *2*(3), 284-299.

Glavee-Geo, R., Shaikh, A.A., Karjaluoto, H., Hinson, R.E. (2019). Drivers and outcomes of consumer engagement: insights from mobile money usage in Ghana. *International Journal of Bank Marketing*, 38, 1-20. doi: 10.1108/IJBM-01-2019-0007.

Harvey, A. C. (1984). Time series forecasting based on the logistic curve. *Journal of the Operational Research Society*, 35(7), 641-646.

Harvey, A. C. (1990). *The econometric analysis of time series*. The MIT Press.

Hu, Z., Ding, S., Li, S., Chen, L., Yang, S. (2019). Adoption intention of fintech services for bank users: An empirical examination with an extended technology acceptance model. *Symmetry*, 11(3), 340.

Jha, A., Saha, D. (2020). Forecasting and analyzing the characteristics of 3G and 4G mobile broadband diffusion in India: A comparative evaluation of Bass, Norton-Bass, Gompertz, and logistic growth models. *Technological Forecasting and Social Change*, 152, Article 119885.

Jiang, Y., Ahmad, H., Butt, A. H., Shafique, M. N., Muhammad, S. (2021). QR digital payment system adoption by retailers: the moderating role of CoViD-19 knowledge. *Information Resources Management Journal*, 34(3), 41-63.

Karjaluoto, H., Glavee-Geo, R., Ramdhony, D., Shaikh, A.A., Hurpaul, A. (2021). Consumption values and mobile banking services: understanding the urban–rural dichotomy in a developing economy. *International Journal of Bank Marketing*, 39(2), 272-293. Doi: 10.1108/ IJBM-03-2020-0129.

Kucharavy, Dmitry, Roland De Guio. (2011). Application of S-shaped curves. *Procedia Engineering*, 9, 559-572.

Kumar, N. K. and Yadav, A. S. (2022). A Systematic literature review and bibliometric analysis on mobile payments. *Vision*, 1-16. DOI: 10.1177/09722629221104190.

Lashitew, A. A., van Tulder, R., Liasse, Y. (2019). Mobile phones for financial inclusion: What explains the diffusion of mobile money innovations? *Research Policy*, 48(5), 1201-1215.

Liébana-Cabanillas, F., Ramos de Luna, I., Montoro-Ríos, F. J. (2015). User behaviour in QR mobile payment system: the QR Payment Acceptance Model. *Technology Analysis & Strategic Management*, 27 (9), 1031-1049.

MacVaugh, J., Schiavone, F. (2010). Limits to the diffusion of innovation: A literature review and integrative model. *European Journal of Innovation Management* 13(2), 197-221.

Mansfield E. (1961). Technical change and the rate of imitation. *Econometrica*, 29(4), 741- 766.

Martino, J. P. (2003). A review of selected recent advances in technological forecasting. *Technological Forecasting and Social Change*, 70(8), 719-733.

Meade, N., Islam, T. (1995). Forecasting with growth curves: An empirical comparison. *International Journal of Forecasting*, 11(2), 199-215.

Meade N. & Islam T. (1998). Technological forecasting - model selection, model stability, and combining models. *Management Science*, 44(81), 115-1130.

Mohamed, Zaid, Bodger, Pat. (2005). A comparison of Logistic and Harvey models for electricity consumption in New Zealand. *Technological Forecasting and Social Change*, 72(8), 1030-1043.

NAD. *National Accounts Data*, Central Statistics Office, Ministry of Statistics and Programme Implementation, Government of India. Retrieved from: https://www.mospi.gov.in/web/mospi/download-tables-data/-/reports/view/templateOne/16701?q=TBDCAT (2022).

NCP. *Population Projections for India and States 2011 - 2036*, National Commission on Population, Ministry of Health & Family Welfare, Government of India. Retrieved from: https://main.mohfw.gov.in/sites/default/files/Population%20Projection%20Report%2020112036%20%20upload_compressed_0.pdf (2022). (accessed on 2 November 2022)

Nieto, Mariano., Lopéz, Francisco, Cruz, Fernando. (1998). Performance analysis of technology using the S curve model: the case of digital signal processing (DSP) technologies. *Technovation*, 18(6-7), 439-457.

NPCI. UPI Product Statistics, National Payments Corporation of India (NPCI). Retrieved from: https://www.npci.org.in/what-we-do/upi/product-statistics (2022). (accessed on 2 November 2022)

ISSN 2683-1007 (Online)
https://journal.access-bg.org/

Panik, M. J. (2014). *Growth curve modeling: Theory and applications*, Wiley.

Ramdhony, D., Munien, S. (2013). An investigation on mobile banking adoption and usage: A case study of Mauritius. *World Journal of Social Sciences*, *3*(3), 197-217.

Ramos de Luna, I., Liébana-Cabanillas, F., Sánchez-Fernández, J., Muñoz-Leiva, F. (2019). Mobile payment is not all the same: The adoption of mobile payment systems depending on the technology applied. *Technological Forecasting and Social Change*, 146, 931-944.

Rogers, Everett M., Arvind Singhal, Margaret M. Quinlan. (2014). Diffusion of innovations. In, *An integrated approach to communication theory and research*, Routledge, 432-448.

Shaikh, Aijaz A., Alamoudi, H., Alharthi, Majed and Glavee-Geo, R. Advances in mobile financial services: a review of the literature and future research directions. *International Journal of Bank Marketing*, 0265-2323. DOI 10.1108/IJBM-06-2021-0230.

Shi, Yuwei, Herniman, John. (2022). The role of expectation in innovation evolution: Exploring hype cycles. *Technovation*, Article 102459.

Singh, S. K. (2008). The diffusion of mobile phones in India. *Telecommunications Policy*, 32(9-10), 642-651.

Sivathanu, B. (2019). Adoption of digital payment systems in the era of demonetization in India: An empirical study. *Journal of Science and Technology Policy Management*, 10(1), 143-171.

TRAI. *The Indian Telecom Services Performance Indicators*, Telecom Regulatory Authority of India (TRAI). Retrieved from: https://www.trai.gov.in/sites/default/files/QPIR_05052022.pdf. (2022) (accessed on 2 November 2022)

Turk, T., P. Trkman. (2012). Bass Model Estimates for Broadband Diffusion in European Countries. *Technological Forecasting and Social Change*, 79, 85–96.

UNCTAD, U. (2019). Digital economy report.

Van Lente, Harro, Arie Rip. (2017). Reflexive co-evolution and governance patterns. *Embedding New Technologies into Society*. Jenny Stanford Publishing, 17-33.

Worldline. *India Digital Payments Report (2021)*. Retrieved from: https://worldline.com/content/dam/worldline/documents/india/documents/worldline-india-digital-payments-report-q1-2021.pdf (2022) (accessed on 2 November 2022)

Zhu, Q., Lyu, Z., Long, Y., Wachenheim, C. J. (2021). Adoption of mobile banking in rural China: Impact of information dissemination channel. *Socio-Economic Planning Sciences*, Article 101011.

About the Authors

Sanjay Kumar SINGH

Dr., Professor in the Business Environment Area at the Indian Institute of Management Lucknow. Dr. Singh is recipient of the NASI-Scopus Young Scientist Award in the area of social sciences for the year 2014, as well as the Manas Chatterji Award for Excellence in Research in Regional Science for the year 2006.

Research interests: applied economics, technology and innovation, industrial economics, infrastructure

ORCID ID: https://orcid.org/0000-0003-0169-1141

Shivendra Sanjay SINGH
He is a young aspiring scholar in the area of economics and financial research. He is currently a final year graduation student enrolled in the Economic and Finance Research program at Shiv Nadar University, NCR Delhi, known as one of the institutes of eminence by the Government of India.

Research interests: financial economics, applied economics, technology and innovation

ORCID ID: https://orcid.org/0000-0001-7611-4344

Vijay Lakshmi SINGH
Dr., Associate Professor at the Jaipuria Institute of Management Lucknow. She earned her doctoral degree from the Indian Institute of Management Ahmedabad. Dr Singh has qualified the Government of India–University Grants Commission's National Eligibility Test for Lecturer and Research Fellowship.

Research interests: industrial organization, technology and innovation, applied economics

ORCID ID: https://orcid.org/0000-0001-5361-4741