Original Article

Toward Inclusive Finance: Mapping Digital Disparities Across India

Journal of Emerging Market Finance
1–22

DOI: 10.1177/09726527251392740
journals.sagepub.com/home/emf
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Abstract

We draw upon a recently released, large-scale dataset to conduct an empirical analysis of the determinants underlying regional disparities in digital payment technology adoption in India. Older individuals and women are less likely to adopt these technologies. Educational attainment plays a significant role. While caste and religion do not directly influence digital payment usage, their effects appear to be mediated through education and economic access. A counterintuitive finding is that economically advanced states such as Chandigarh, Delhi, Gujarat, and Karnataka have relatively low adoption of digital payment systems. Individuals prefer to conduct high-value transactions in cash to evade paying income tax.

Keywords

Digital payments, digital infrastructure, demographic factors, digital divide, regional disparity

JEL Codes: C3, E7, G2

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1. Introduction

In recent times, financial inclusion has gained significant attention as a development objective among policymakers, both in India and globally. Financial inclusion is crucial for creating business opportunities, ensuring efficient resource allocation, and facilitating the delivery of various social welfare programs (Khuntia, 2014). It can promote economic growth (Kumar Lenka & Sharma, 2017) and reduce poverty and income inequality (Zhang & Posso, 2019). One way to promote financial inclusion is by establishing a robust digital finance infrastructure. Digital payment systems have become a transformative force in modern financial ecosystems, reshaping how transactions are conducted, financial services are accessed, and economies operate.[1] A growing body of literature emphasizes their relevance in enhancing efficiency, promoting transparency, and driving financial inclusion. A variety of payment methods fall into the category of digital payments, for example, mobile QR-code payments and wallets, online transfers, e-wallets, and central bank digital currencies (Botta & Nadeau, 2022).[2] Given the rapid digitalization of financial services in India, this article examines the adoption of digital payment technology in the country.

The motivation to study the adoption of digital payments stems from several factors. First, India has undergone rapid digitalization in recent years. The creation of digital public infrastructure such as India Stack (n.d.) has been crucial in driving financial inclusion and digital payment adoption in the country.[3] As of January 2025, approximately 1.12 billion active cellular mobile connections were recorded, representing 76.6% of the population—the highest penetration rate to date. Concurrently, around 806 million Indians, or 55.3% of the population, were active Internet users in 2024, marking a 6.5% increase from the previous year, which was an all-time-high growth rate (Kemp, 2025). The spread of the Internet and mobile phones has helped India achieve a leadership position in digital payments, with the Unified Payments Interface (UPI) accounting for 48.5% of the global payment volume (Reserve Bank of India, 2025). In the second half of 2024, UPI recorded 93.23 billion transactions, reflecting a 42% year-on-year, amounting to ₹130.19 trillion in value (Worldline, 2025).[4] There is a need to understand how digitization has impacted financial inclusion in India, which this study attempts to address.

Second, the adoption of digital payment infrastructure can be successful only if people have access to bank accounts. In 2014, the Government of India (GoI) launched the Pradhan Mantri Jan Dhan Yojana (PMJDY) as a key supply-side initiative to promote financial inclusion among the unbanked and ensure effective monitoring of government welfare fund transfers. However, assessing the impact of supply-side interventions, such as PMJDY, on financial inclusion presents two key challenges. First, individuals may hold multiple bank accounts, and using data, such as the number of bank branches per thousand population, could lead to overestimation. Second, merely opening a bank account does not necessarily indicate active usage by the account holders. Globally, approximately 15% of bank accounts remain dormant (Demirgüç-Kunt et al., 2015). Empirical evidence suggests that the relationship between the supply of institutional finance and its demand is relatively weak in India (Kamath et al., 2010). Against this background, it becomes imperative to undertake an analysis that focuses on the impact of demand-side interventions in advancing financial inclusion in India. This article undertakes such an analysis by examining factors that lead to the adoption of digital payment technology, which is an outcome of demand-side interventions, in India.

Finally, works done on this subject were based on surveys that either were conducted online (Shree et al., 2021) or, if offline, were limited to a few cities (Sinha et al., 2019). When a survey is conducted online or limited to certain geographic areas (e.g., metropolitan cities), it may capture responses only from specific demographic groups, potentially limiting the generalizability of findings. Such a survey also tends to have a small sample size, usually around 400 data points. Consequently, the conclusions derived from such a survey have limited generalizability and scalability and may suffer from small-sample bias (Cohen, 1988). Our study attempts to fill this gap in the literature. For the first time, this article analyzes the impact of factors such as digital infrastructure and economic well-being on the adoption of digital payments in India. We utilize a large unique dataset evenly distributed across 23 states and union territories, encompassing both urban and rural areas in 160 districts. Since our analysis is based on a large, nationally representative sample, our results are statistically more reliable than those reported in the existing literature. The wide geographical reach of our sample enables us to identify regional disparities in the adoption of digital payment technologies. Our findings can assist policymakers in identifying states and union territories that have lower adoption rates of digital payment technologies, as well as the factors contributing to this variation across India.

The rest of the article is organized as follows. Section 2 reviews the existing research on the financial relevance of digital payment infrastructure. In Section 3, we describe the data, followed by the methodology, presented in Section 4. We discuss our results and their implications in Section 5. Finally, we conclude with policy implications in Section 6.

2. Literature Review

The widespread adoption of digital payment tools can have substantial positive impacts on the economy of a country. Several studies have highlighted the role of digital payments in reducing transaction costs and increasing the speed and security of financial transactions (Beck et al., 2022). Digital platforms lower overheads associated with cash handling, reduce the risks of theft or loss, and streamline payment processing for both businesses and consumers. This operational efficiency can foster greater economic productivity. For example, the cost of dealing with cash can be between 5% and 10% of the total operating costs of banks (Brugge et al., 2018). Banks can reduce this cost by encouraging their customers to adopt digital payment methods. The rise in global trade requires large inter-bank transactions to be settled quickly with minimum transaction charges. Digital payment methods are being adopted globally to satisfy these emerging needs (Calderon, 2025).

The presence of digital payment infrastructure plays a crucial role in the development of broader financial markets. According to Frost et al. (2021), digital transactions facilitate more data-driven credit assessment models, enabling the expansion of credit access, particularly to micro, small, and medium enterprises (MSMEs). By creating a verifiable history of transactions, digital payments can help MSMEs improve record-keeping and gain access to credit through the formal financial system (Jack et al., 2010).

The growth of digital payment infrastructure can spur economic growth in the country by increasing access to financial services such as credit, savings, and investments (Marashdeh & Al-Malkawi, 2014). The adoption of digital payment services such as M-PESA lifted 2% of the Kenyan population out of poverty by changing their financial behavior, for example, by incentivizing them to save and move out of agricultural occupations (Suri, 2017; Suri & Jack, 2016). Digital payment technologies can reduce barriers to entry for underserved populations by minimizing reliance on traditional banking infrastructure (Demirgüç-Kunt et al., 2022).

Apart from economic benefits, digital payment methods also provide traceability, which can lead to improved tax collection (Bohne et al., 2023;

Joseph & Ramalingam, 2023). By creating digital trails, electronic payments help governments broaden the tax base and enhance revenue collection. Evidence from India's demonetization and digital push indicates an increase in formal transactions, contributing to better tax compliance (Rogoff, 2017). These systems also assist in the disbursement of government subsidies and welfare programs, improving targeting and reducing leakages. Therefore, governments also encourage their citizens to use digital payment methods as much as possible.

2.1. Digital Payment Infrastructure in India

Digital payment infrastructure in India has rapidly evolved, supported by a growing smartphone user base and affordable Internet data. UPI is significantly benefiting MSMEs in India by providing a simple, fast, and cost-effective payment system. It enables businesses to accept payments digitally without the need for expensive infrastructure like card-swiping machines. UPI transactions are instant and can be conducted via smartphones, making UPI accessible for small shopkeepers and vendors. With low transaction fees and wide acceptance, UPI has helped small businesses expand their customer base, improve cash flow, and enhance operational efficiency. Importantly, by creating credit histories from cash-flow data through UPI transactions, digital payments are democratizing access to credit for smaller businesses. In India, there are 63 million MSME businesses, but only 14% have access to credit (Khan, 2025). Most MSMEs lack documented cash-flow statements, making it difficult for banks to extend credit to them. The GoI chose to keep the UPI transactions free of cost for it to become widespread. The GoI is also intensifying its efforts toward the internationalization of UPI by developing interoperable frameworks and expanding global payment acceptance. Data from the National Payment Corporation of India (NPCI), GoI, show that the daily transactions during April 2025 were between 530 and 630 million, with a value of over ₹570–₹1,020 billion. Between fiscal years 2019–2020 and 2024–2025, UPI transactions registered a compound annual growth rate of 72%. As illustrated in Figure 1, the number of transactions settled through UPI increased significantly between 2016 (the year of its launch) and 2024.

The digital revolution illustrated in Figure 1 has been driven by both demand- and supply-side factors. Supply-side factors include technological innovations, policy interventions, and better infrastructure. On the other hand, the demand for digital payment methods was reinforced by two events. The first event was the demonetization of the ₹500 and

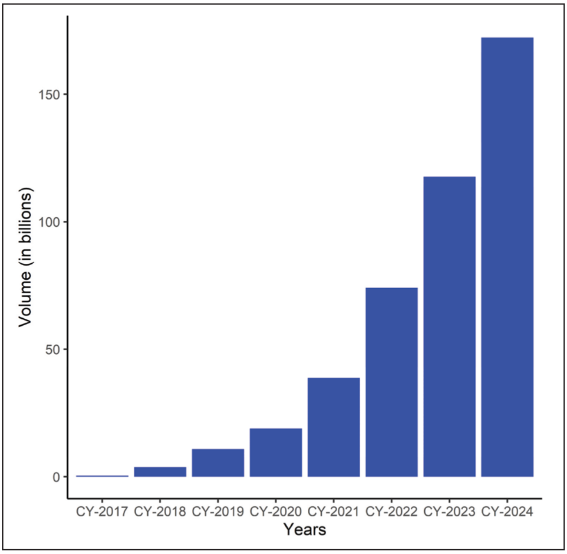

Figure 1. Volume (Number of UPI Transactions) Between Calendar Years (CY) 2016 and 2024.

Source: NPCI, UPI Statistics (n.d.).

₹1,000 banknotes, which took place in November 2016. This led to a shortage of cash in the economy and an increase in digital transactions (Sobti, 2019). The second event was the COVID-19 pandemic, which discouraged people from making physical transactions due to the fear of getting infected with the virus. This fear led people to engage in more contactless digital transactions (Singhal & Gupta, 2021).

Despite the positive influences of the aforementioned factors, India continues to remain predominantly a cash-based economy. India's cash-to-GDP ratio is the third highest in the world, behind those of Japan and Hong Kong (Shetty, 2022). The problem of low adoption of digital payments has been examined by several studies in the literature; the majority of which approach the issue from the psychological perspective of an individual user. Using concepts developed in the fields of psychology, sociology, and behavioral sciences, these studies focus on understanding factors that affect the decision-making process of any individual. For example, using the valence-TACT models, Pal et al. (2021) identified factors such as convenience, reflection, and security that impact the actual usage and future intentions to use digital payments. Similarly, Patil et al. (2020) employed the meta-UTAUT model and found that performance expectancy, the intention to use, and grievance redressal significantly and positively influence consumer behavior in the adoption of mobile payments. A closely related study by Srivastava et al. (2024) suggests that customer satisfaction, effort expectancy, and performance expectancy significantly impact the intention to use digital payment technologies. Such studies provide valuable insights into factors evaluated by consumers when deciding to adopt a digital payment method. The findings of such studies help policymakers design policies that will encourage individual users to adopt digital payments, for example, by making digital transactions cheap, reliable, and convenient. However, these studies assume that individuals have access to all the necessary resources, such as access to a mobile phone and Internet connectivity, to make digital payments, which may not be the case in a lower-middle income country like India.

In India, people may also struggle with the skills necessary to effectively use digital payment technologies. Financial and digital literacy significantly influence the adoption of digital payment technologies. Digital literacy, encompassing the ability to navigate digital platforms, and financial literacy, the understanding of basic economics and finance for personal financial decisions, are critical drivers of adoption. Thus, both literacies are essential for effective engagement with digital payment systems (Lo Prete, 2022). Jayaraman and Jambunathan (2018) find that the level of financial literacy is low among school-going children in India, which may also affect their ability to adopt digital payment technologies later in their lives. Familiarity with mobile financial services, confidence in their reliability, proximity to service agents, and assurance of data privacy are key factors likely to encourage the use of mobile financial services (Dziwornu et al., 2018).

Additionally, there are infrastructural requirements. To facilitate the adoption of digital payment infrastructure, four foundational components are essential (Putrevu & Mertzanis, 2024): first, a steady supply of electricity; second, access to affordable information and communication technology infrastructure such as smartphones and cellular data tariffs; third, financial infrastructure such as payment exchanges, clearing and settlement systems, and data-sharing and data-hosting facilities; and, fourth, a digital identification infrastructure to provide proof of identity and associated credentials. The GoI, through its India Stack, has done well in fulfilling the last two infrastructural requirements. However, access to a regular supply of electricity, affordable smartphones, and affordable data plans can still be a challenge in many parts of the country. Literacy programs specifically aimed at women can significantly enhance the accessibility and coverage of the formal financial system (Khandelwal et al., 2025).

For our exploratory data analysis, we select the variables from the aforementioned literature that are expected to have an impact on the adoption of digital payment.

3. Data

In this study, we use the 2021 edition of the ICE 360 dataset (PRICE, n.d.), which provides household-level data on the well-being of Indian households, such as their financial, living, and working conditions. Additionally, data on the demographic profiles of all members of the household are also available. This survey was conducted between January and June 2021. The survey used stratification and probability sampling techniques to obtain an accurate representation of the Indian population. The population of a given state was divided into urban and rural categories based on the proportions reported in the 2011 Census. For identifying any household, the electoral rolls were used. The adults within any particular household were chosen based on the Kish Grid method.[5] After the first interview, every fifth household in the urban areas and every third household in the rural areas were selected as a subsequent household, following the right-hand rule.[6] A total of 40,427 household data points were collected across India, proportionate to the size of the adult population (above 18 years of age) in the respective states. The survey provides a good representation of all demographic groups (e.g., caste, religion, gender, age, and education) and geographies (rural and urban areas of 23 states and union territories) of the country. Consistent with the findings in the existing literature, we observe that the adoption of digital payments remains low in India. In our dataset, only 18% of the respondents reported using digital payment methods. The summary statistics from the survey are reported in Table 1.

4. Methodology

This section outlines the methodology used to identify the demographic groups and geographic regions that contribute to variations in digital payment adoption across India. Our analysis considers access to electricity, feature phones, smartphones, the Internet, and bank accounts as essential

Table 1. Summary Statistics of All Variables in the Dataset.

Total number of data points	40,427	
Digital payment	Yes	10,882 (26.92%)
	No (Base)	29,545 (73.08%)
Gender	Female	18,925 (46.81%)
	Male (Base)	21,502 (53.19%)
Level of education	Illiterate (Base)	5,861 (14.50%)
	Up to middle school	15,608 (38.61%)
	Up to higher secondary school	14,154 (35.01%)
	Graduate and above	4,804 (11.88%)
Social group	Schedule Caste (Base)	11,141 (27.56%)
	Schedule Tribe	2,961 (7.32%)
	Other Backward Classes	16,066 (39.75%)
	Others	10,259 (25.38%)
Access to a bank account	Yes	33,420 (82.67%)
	No (Base)	7,007 (17.33%)
Access to the Internet	Yes	22,893 (56.63%)
	No (Base)	17,534 (43.37%)
Type of mobile phone	No mobile phone (Base)	14,480 (35.82%)
	Smartphone	19,836 (49.07%)
	Feature phone	6,111 (15.12%)
Age	First quartile	26
	Median	34
	Third quartile	45
Hours of electricity	First quartile	20
	Median	22
	Third quartile	24
Religion	Hindu (Base)	34,747 (85.95%)
	Muslim	3,450 (8.53%)
	Sikh, Jain, and others	1,632 (4.04%)
	Christian	598 (1.48%)

Note: "Base" refers to the reference category used in our probit regression analysis. The number of data points across each state is reported in Table A2.

infrastructure for digital payments. In addition, we include demographic variables such as age, gender, and education to account for demographic differences. To address selection bias, which we explain below, we employ a two-step probit regression analysis.

As part of the ICE 360 household survey, the chief wage earner of the household was asked "Do you use any digital payment methods (PayTM, PhonePe, BHIM, AePS, and G-Pay)?" The respondent, that is, the chief wage earner of the household, could respond with either a "yes" or a "no." We used the respondent's answer to this question to create a binary variable (DigiPay) that indicates whether the survey respondent uses digital payments or not.

We note that having access to a bank account is necessary for conducting digital payments. Consequently, individuals without a bank account are not observed to adopt digital payments. This creates a sampling bias in our analysis. To correct for this sampling bias, we use the sample selection model developed by Heckman (1979). Although Heckman originally developed this model for linear regressions, his model has been extended to probit regressions as well. We use the implementation of Tobit 2 sample selection models for binary dependent variables by Toomet and Henningsen (2008) in the R programming language. This method requires a two-step estimation process. In the first step, the selection equation is estimated. In our case, this step involves estimating a probit regression model, with the dependent variable ($BankAcc_i$) indicating whether the individual i (chief wage-earning member of the household) has access to a bank account or not. Mathematically, we estimate the following regression:

$$P[BankAcc_i = 1] = \Phi(\alpha + x_i'\beta + \epsilon) \tag{1}$$

where $\Phi(\cdot)$ denotes the cumulative distribution function (CDF) of the standard normal distribution. The vector x_i includes data on the respondent's (chief wage earner (CWE) of the household i) demographic profile and their access to various resources needed for the adoption of digital payments. The list of demographic variables includes the respondent's age, gender, level of education, religion, and social group. Variables such as daily hours of electricity, mobile phone type, and Internet access indicate the resources needed for digital payment. The selection of independent variables draws from the literature discussed in Section 2. We report the results of this regression in Table 2.

Subsequently, we estimate the outcome equation, in which the dependent variable ($Digipay_i$) is an indicator variable that denotes whether or not the CWE of the household i uses digital payment technologies. Mathematically, we estimate the following equation:

$$P[Digipay_i = 1] = \Phi(\alpha + x_i'\beta + \epsilon) \tag{2}$$

where $\Phi(\cdot)$ and x_i are described as in Equation 1. Note that in Equation 2, the inverse Mills ratio is included as a covariate to correct for the selection bias (reported as ρ in Table 2). The inverse Mills ratio is the ratio

Table 2. Results of the Sample Selection Model with a Binary Outcome (Tobit 2).

	Dependent Variable: Access to Bank Account (Equation 1)		Dependent Variable: Digital Payment (Equation 2)		
Term	Estimate	Std. Error	Estimate	Std. Error	AME
Intercept	−1.4495	0.096***	−3.0312	0.2111***	–
Age	0.0564	0.0033***	0.0377	0.0045***	0.0066
Age^2	−0.0004	0***	−0.0004	0.0001***	−1.00E–04
Gender: Female	0.2127	0.0175***	−0.4116	0.0215***	−0.0697
Hours of electricity received in a day	0.0018	0.0019	−0.0005	0.0021	−0.0002
Access to Internet	0.8387	0.0242***	1.0250	0.0606***	0.1595
Education					
Up to middle school	−0.3337	0.0262***	−0.0323	0.0470	−0.0058
Up to higher secondary	−0.0264	0.0293	0.3399	0.043***	0.0548
Graduate and above	0.0350	0.0439	0.8618	0.0461***	0.1622
Religion					
Muslim	0.0707	0.0329*	0.0159	0.0350	0.004
Sikh	0.0482	0.0630	0.1532	0.0678*	0.0267
Christian	−0.0873	0.0736	−0.0637	0.0755	−0.0082
Others	0.0000	0.0748	0.2718	0.0806***	0.05
Social group					
Scheduled Tribe	0.0076	0.0365	−0.0286	0.0406	−0.0042
Other Backward Castes	0.0199	0.0221	−0.0165	0.0247	−0.0026
Others	0.0287	0.0244	−0.0674	0.0271*	−0.0111
Mobile type					
Smartphone	0.8977	0.0275***	0.9792	0.0737***	0.1578
Feature phone	0.8180	0.023***	0.1915	0.0775*	0.0332
State					
Assam	0.3492	0.0824***	−0.1473	0.0848.	−0.0212
Bihar	0.3145	0.0611***	−0.1338	0.0686.	−0.0209
Chandigarh	0.1967	0.1089.	−0.2471	0.1236*	−0.036

(Table 2 continued)

(Table 2 continued)

Term	Dependent Variable: Access to Bank Account (Equation 1) Estimate	Std. Error	Dependent Variable: Digital Payment (Equation 2) Estimate	Std. Error	AME
Chhattisgarh	0.2995	0.0683***	−0.2162	0.0782**	−0.033
Daman & Diu	0.3447	0.1245**	0.0061	0.1450	0.0046
Delhi	0.3999	0.0683***	−0.1585	0.0756*	−0.0249
Gujarat	0.3598	0.0594***	−0.3154	0.0644***	−0.046
Haryana	0.2934	0.0643***	−0.1015	0.0694	−0.0145
Himachal Pradesh	0.1623	0.0843.	−0.1615	0.0954.	−0.0228
Jharkhand	0.2833	0.0718***	−0.0621	0.0748	−0.008
Karnataka	−0.0200	0.0564	−0.1654	0.059**	−0.0246
Kerala	0.2268	0.0645***	−0.0623	0.0666	−0.0102
Madhya Pradesh	0.5795	0.0685***	−0.3406	0.0692***	−0.05
Maharashtra	0.1796	0.053***	0.0551	0.0554	0.0112
Odisha	0.4999	0.0666***	−0.0949	0.0715	−0.0128
Punjab	0.3448	0.0637***	−0.0154	0.0696	0.0008
Rajasthan	0.2048	0.0627**	−0.2910	0.0715***	−0.0444
Tamil Nadu	0.1251	0.0533*	0.0919	0.0542.	0.0171
Telangana	0.2079	0.0605***	0.1123	0.0616.	0.0226
Uttar Pradesh	0.2463	0.0534***	−0.2208	0.0566***	−0.0347
Uttarakhand	0.2064	0.0918*	−0.0601	0.1010	−0.0071
West Bengal	0.2549	0.0541***	−0.1944	0.0589***	−0.0287
ρ	–	–	−0.0320	0.2071	–

Notes: Significance codes: 0 "***" 0.001 "**" 0.01 "*" 0.05 "." 0.1 " " 1.
Maximum likelihood estimation; log likelihood: −25,601.94.

of the probability density function and the CDF of the standard normal distribution. It is calculated for each observation in the selected sample using the estimated parameters from Equation 1. It is used to correct for the bias that arises when the sample is not random but instead is selected in a way that depends on the outcome of an underlying latent variable.

4.1. Robustness Checks

To check the robustness of our results, we performed sensitivity analysis as outlined in Levine and Renelt (1992). The idea was to see whether estimation through a different methodology affects the regression outcome. The coefficient of a variable originally considered is robust if its sign and level of significance do not change. For this purpose, we conducted a logistic regression analysis, with the results reported in Table A1. We found that the significance levels and the signs of the regressors remained consistent, indicating the robustness of our results. We also conducted robustness checks to ensure that our results are not sensitive to the list of independent variables included in the model. In this regard, we eliminated one variable at a time and observed the changes in the sign and level of significance for coefficients of other variables. Here also, we did not observe any change indicating the robustness of our results. Since most of the variables in our model are categorical, multicollinearity is not a significant concern.

The problem of heteroskedasticity is minimal since the dependent variable is categorical. In linear regression, heteroskedasticity occurs when the variance of the error term is not constant across all levels of the independent variables. However, for models with a categorical dependent variable such as logistic and probit, heteroskedasticity is inherently accounted for in the model's fundamental assumptions. For a binary outcome, the variance of the errors is given by $p(1-p)$, where p is the predicted probability. Since the variance changes with the predicted probability, which in turn varies with the independent variables, the model is heteroskedastic by design.

5. Results and Discussion

As mentioned in Section 4, we used a sample selection model with binary dependent variables to explain the variation in the adoption of digital payment technologies. The results are presented in Table 2, which provides the estimate of the outcome equation along with the average marginal effect (AME) of each independent variable on the dependent variable (calculated separately).[7] As described in Table 2, coefficients of both age and age^2 are significant, indicating the existence of a nonlinear relationship between age and the adoption of digital payments. The negative coefficient of age^2 suggests that older people are less likely to adopt digital payment technologies. We found a significant relationship between gender and the inclination to use digital payment technologies. We also found that women, on average, are 7% less likely to adopt digital payment technologies compared to men. This gender gap, initially documented by Ghosh and Vinod (2017), persists. The level of education attained by any person also plays an important role in determining the adoption of digital payments. We found that people with higher secondary education are 5.48% more likely to use digital payments compared to those without education. Similarly, people who have studied to the graduate level and above are 16.22% more likely to use digital payments than those without education. However, education up to the middle school does not appear to be significantly helpful in influencing individuals toward the adoption of digital payments. Our results show that education helps people acquire digital literacy skills and makes them more inclined to use digital payments. These results are consistent with the literature (Mukhopadhyay, 2021; Shree et al., 2021).

We could not find any notable variation in the usage of digital payments across different religions and social groups. We suspect that the reason for this could be that religion and caste do not directly impact digital payment adoption, but they make an impact through other variables. For example, religion and caste have been reported to affect access to education (Borooah & Iyer, 2005) and economic resources (Munshi, 2019). Since we have already included these variables (access to education, bank account, Internet, smartphones, and electricity) in our model, we assume that the effects of caste and religion have already been considered by these variables. However, financial products and interventions aimed at influencing specific financial behaviors must consider the diverse family structures across India (Kurian et al., 2022).

Next, we discuss how access to different resources, such as electricity, Internet, and smartphones, affects the adoption of digital payment methods. We found that the number of hours a household receives electricity in a day is not significantly related to the adoption of digital payments by its CWE. An uninterrupted supply of electricity is more critical for banking services such as ATMs. However, most of the digital payments are completed on mobile phones, which do not require a continuous supply of electricity to function. This may be the reason for the insignificant relationship between the two variables. Although there are digital payment techniques available in India that do not require an Internet connection to complete a transaction, for example, UPI Offline (NPCI Offline UPI, n.d.) and Aadhar-enabled Payment System (NPCI AePS, n.d.), having an Internet connection surely makes it more convenient. We found that, on average, people with access to the Internet are 16% more likely to use digital payments compared to those without it. Similarly, even though digital payment techniques such as AePS do not require a mobile phone to complete a transaction, having access to a mobile phone increases the probability of using digital payments. We found that having a feature phone increases the probability of digital payments by 3.3%, whereas having a smartphone increases the probability of digital payments by 15.8%.[8] Note that a person who has access to all the resources required for digital payments will not necessarily use it. In other words, access to resources discussed above is a necessary, but not sufficient, condition for the adoption of digital payments.

Finally, we discuss geographical regions that are lagging in the adoption of digital payment technologies. For this purpose, we include the state/union territory in which the household was residing as an independent variable in the model. Andhra Pradesh is treated as the base category. Therefore, the AME of a state shows how much more or less likely its households are (on average) to use digital payments in comparison to Andhra Pradesh.[9] In our analysis, five states with the highest digital payment adoption are Telangana, Tamil Nadu, Maharashtra, Daman and Diu, and Andhra Pradesh. In contrast, the five states with the lowest adoption are Madhya Pradesh, Gujarat, Rajasthan, Chandigarh, Uttar Pradesh, and West Bengal. Interestingly, we identified some financially well-off states with a lower adoption of digital payments. For example, Gujarat (−4.6%), Chandigarh (−3.6%), Karnataka (−2.5%), and Delhi (−2.49%) are lagging in the adoption of digital payments.[10]

Ideally, economically progressive states are expected to have better Internet connectivity, higher smartphone penetration, advanced financial infrastructure, and a more literate population, which may lead to a greater adoption of digital financial infrastructure and use of UPI. A possible explanation of this counterintuitive results, which is low adoption of digital payment infrastructure, may be because of two possible reasons. First, businesses in economically advanced states tend to involve high-value transactions. For UPI-related transactions, there is an upper limit of ₹0.1 million on daily transactions. This decrease is primarily attributed to the growth in person-to-merchant transactions, which are typically of smaller value. As per the India Digital Payments Report published by Worldline (2025), for the first half of 2024, the average ticket size for all UPI transactions declined by 8% compared to the same period in 2023, dropping from ₹1,603 to ₹1,478. As per a letter by the NPCI to all UPI member banks in 2022, 75% of the total volume of retail transactions (including cash) in India are below ₹100, and 50% of the total UPI transactions have a value of up to ₹200 (Kalawatia, 2022). Economically well-off states with a higher per-capita income may have a relatively smaller proportion of such transaction. Second, this may be because vendors in states with lower digital payment adoption are reluctant to accept UPI transactions out of concern for potential tax liabilities. Ligon et al. (2019) also found a similar result in their study, where merchants in Jaipur city in Rajasthan avoided accepting digital payments in anticipation of an increased tax liability. Many economic activities involving real estate transactions, visits to doctors, and other white-collar professionals such as chartered accountants often prefer cash payments (Reserve Bank of India, 2025). A survey indicated that approximately 44% of real estate transactions involved cash payments. Notably, 8% of respondents admitted to paying over 50% of the property's value in cash, highlighting significant underreporting of actual transaction amounts (Moneycontrol, 2022). In the fiscal year 2023–2024, only 6.68% of Indians filed income tax returns, with only 2% of Indians actually paying tax (PTI, 2024; Tiwari, 2025).

6. Conclusions

Our study used a large, nationally representative dataset and provides new insights into the regional disparities in the adoption of digital payment technologies in India. Our results indicate that several demographic factors, including age, gender, and education, significantly influence the adoption of digital payment technologies. Elderly individuals are less likely to adopt digital payment technologies, and the adaptivity for digital technology tends to fall as people become old. Gender gap persists, with women being less likely than men to adopt digital payments. Education also plays a crucial role, with higher levels of education correlating with a greater likelihood of digital payment usage. Specifically, individuals who have attained higher secondary education or above are significantly more likely to adopt digital payments. Economic well-being plays a critical role, too, as people with higher incomes or stable financial conditions are more likely to own smartphones, access the Internet, and invest time in learning new technologies. In contrast, those in lower-income groups or with limited economic resources may face barriers, such as lack of access to technology or the Internet, which hinders their ability to adopt digital payments. Caste and religion, while important aspects of social identity, do not significantly influence the adoption of digital payment technologies. We suspect that caste and religion influence digital payment adoption indirectly, primarily through factors such as education and economic access, which are already captured by variables used in our model such as education, bank access, Internet, smartphones, and electricity. Contrary to popular perception, digital payment adoption is not consistently higher in economically progressive states. Digital payment usage is surprisingly lower in some economically advanced states such as Chandigarh, Gujarat, Karnataka, and Delhi. High-value transactions often exceed the amounts that can be sent or received using UPI, thus reducing its use. Additionally, wealthier regions may see fewer low-value merchant payments. Some vendors and economic activities pertaining to real estates also avoid UPI transactions due to tax concerns, contributing to unexpectedly low adoption of UPI in economically progressive areas. To promote the use of digital payment infrastructure, the GoI should consider increasing the daily transaction limit and intensifying efforts toward the internationalization of UPI. The results of our study suggest that economically prosperous states may exhibit lower rates of digital payment adoption, with broader global implications, namely, that affluence alone is insufficient to drive the widespread use of digital payment technologies. In a broader global context, our results show that the benefits of these technologies can be realized substantially only if governments implement targeted initiatives to promote their adoption. A limitation of this study is the absence of financial and digital literacy variables, as they were not included in the survey. Past studies indicate that the adoption of digital payments is strongly influenced by the financial and digital literacy of the population. While we considered formal education levels in our analysis, it is not an effective substitute for financial education, as financial literacy remains low among Indian schoolchildren. This can be explored in future work.

Acknowledgment

The authors are grateful to Professor Balasubramanian G. and two other anonymous referees of the journal for their extremely useful suggestions to improve the quality of the article. The authors would also like to express their sincere gratitude to N. Prathiba Reddy and Shreemayi Gunda for their outstanding support as research assistants.

Author Contribution

Nilanjan Banik: Instrumental in obtaining the ICE 360 data from the People Research on India's Consumer Economy (PRICE); contributed in the literature review and writing of the article.

Pranjal Chandrakar: Conceived the research idea, analyzed data, performed literature review, and wrote the article.

Data Availability

The dataset analyzed during the current study are available from the corresponding author on reasonable request.

Declaration of Conflicting Interests

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

Supplemental Material

Supplemental material for this article is available online.

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Notes

1. Digital payment systems involve conducting transactions using electronic devices and digital channels.
2. Among the various types of digital payments, mobile payments are the most popular.
3. India Stack is a collection of application programming interfaces (APIs) that form the foundation for digital identity (via Aadhaar and DigiLocker), digital payments (through the Unified Payments Interface), and secure data sharing (via electronic–Know Your Customer).
4. One of the unique features of UPI is its use of a virtual payment address (VPA), eliminating the need to share sensitive information like account numbers or IFSC codes. This enhances security and simplifies transactions. Users authenticate payments using a single-click two-factor authentication (2FA), ensuring both convenience and safety.
5. The Kish Grid method is a systematic technique used in survey sampling to randomly select one individual from a household when there are multiple eligible respondents.
6. The right-hand rule in sampling is a simple field technique used to systematically select households during surveys, especially in areas where detailed maps or household lists are not available. The surveyor selects households at a fixed interval (e.g., every third or fifth house), continuing to turn right at intersections or dead ends upon exiting the last surveyed house.
7. AME represents the change in the probability of the dependent event occurring with a one-unit change in an independent variable, while holding other variables constant.
8. Feature phones are limited to calling, texting, and occasionally basic apps such as FM radio, a calculator, or a simple browser. They do not have app stores and typically cannot download any mobile application. On the other hand, smartphones run on full-featured operating systems (e.g., Android or iOS) and support advanced applications. They feature touchscreen interfaces and allow users to download a wide range of apps, including those for digital payments, messaging, and social media.

9. Judging a state or union territory based on its coefficient (or AME) in the probit regression controls for all demographic differences and resource-related constraints across different states.
10. The percentages in parentheses show the average reduction in the probability of a randomly selected individual from that state using digital payments when compared to a randomly selected individual in Andhra Pradesh.

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