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HETEROGENEOUS EFFECTS OF UNIFIED PAYMENT INTERFACE READINESS ON DIGITAL PAYMENT ADOPTION IN INDIA: EVIDENCE FROM CAUSAL FOREST MODELS

Abstract

The rapid expansion of the digital payment system has transformed financial inclusion in India; however, it has not eliminated persistent socioeconomic and spatial disparities in digital financial participation. The Unified Payments Interface (UPI) adoption has been marked by highly uneven adoption across socioeconomic groups, which limits its direct benefits. Using the World Bank's Global Findex 2025 microdata, the machine learning-based causal forest model analyzes the heterogeneous effects of UPI readiness on individual-level digital payment adoption. The results show that UPI readiness has a positive average treatment effect of 0.161 on the digital payment index (0-1 scale). Substantial heterogeneity persists across urban–rural location, income, education, and gender, confirming entrenched digital divides. The most pronounced heterogeneity emerges along an inclusion–exclusion spectrum: individuals facing the greatest affordability and usability constraints experience treatment effects up to 3.7 times larger than the most digitally included groups. The findings point to the need to develop targeted digital inclusion policies for socially vulnerable population groups, aimed at strengthening their financial resilience and expanding their digital engagement. The study also provides novel empirical evidence on the effective use of machine learning methods to inform public finance policies aimed at fostering inclusive digital ecosystems.

Keywords

digitization, financial inclusion, UPI, machine learning, heterogeneity

JEL Classification

O16, G21, C55, D14

INTRODUCTION

Globally, the exponential growth of digital payment technologies has transformed how households and individuals access, use, and benefit from the formal financial system (Demirgüç-Kunt et al., 2020; World Bank, 2021). India is also no exception. In fact, the Unified Payments Interface (UPI) represents one of the most ambitious large-scale digital payment initiatives globally. According to the Reserve Bank of India (RBI)'s Digital Payments Index, digital payment activity has increased sharply, with the index rising more than 4-fold from its 2018 base value to 493.22 in March 2025, indicating deepening adoption supported by robust payment infrastructure and government programs (RBI, 2025). These financial developments are closely linked to broader development objectives, since digital payments serve as a cornerstone of financial inclusion, economic participation, and household resilience to economic and environmental shocks (Chhatre et al., 2023; Suri & Jack, 2016).

Despite this rapid expansion, the benefits of digital payment systems remain unevenly distributed across income, education, gender, and rural–urban groups. Large segments of these socio-economic popula-

tion groups continue to face persistent barriers. Rural residents often encounter poor network coverage and limited merchant acceptance. At the same time, women and low-income households face affordability constraints, lower digital literacy, and sociocultural restrictions that inhibit active participation in digital financial ecosystems. This leads to dualism in formal financial services: on one hand, there is an overall increase in the number of digital transactions, while on the other, there are deep structural divides. Eventually, digitization may reinforce existing financial inequalities rather than reduce them.

The disparity between effective participation in digital payment systems and nominal access to digital financial infrastructure is a major scientific issue arising from this context. Owning a digital device or a formal bank account does not necessarily mean actively engaging in digital transactions. Complex adoption patterns that differ among population groups are produced by the interplay of individual capabilities, institutional access, and technological preparedness. In the study of digital financial inclusion, it is still unclear how readiness to engage in digital payment ecosystems translates into actual usage under diverse socioeconomic circumstances.

1. LITERATURE REVIEW AND HYPOTHESES

The review of literature has emphasized two broad dimensions. First, we have reviewed empirical evidence on India's growth of digital payments in recent years, the benefits from digitization, and persistence gaps in delivering the benefits across gender, spatial, and socioeconomic groups. Secondly, we have emphasized the recent methodological advances concerning the application of interpretable machine learning methods to analyze heterogeneous effects.

Digital financial inclusion plays a crucial role in contemporary development finance as a driver of economic empowerment and poverty alleviation. The wider availability of digital payment platforms and mobile banking services has transformed financial ecosystems globally. This has created opportunities to overcome longstanding geographic, socioeconomic, and gender barriers (Demirgüç-Kunt et al., 2020). The World Bank identifies the rapid UPI-based expansion of digital payments in India as a leading example of large-scale financial technology deployment for strengthening digital financial inclusion (World Bank, 2021). UPI technology has substantially increased transactional capacity, supporting billions of transactions each month, enabling more seamless cashless payments, and reducing dependence on informal financial channels (RBI, 2025).

However, rising account ownership statistics do not necessarily guarantee substantive inclusion

or sustained use of digital financial instruments. Persistent gaps in digital financial usage among women, rural residents, and socioeconomically marginalized groups have been widely documented (Duvendack et al., 2023; Gupta & Kiran, 2024a). Beyond device access, these groups often face multifaceted barriers such as limited digital literacy, privacy and security concerns, low trust levels, and entrenched sociocultural constraints. All these restrict active engagement with digital finance (Banerjee et al., 2013). In fact, sustainable financial inclusion requires not only the necessary infrastructure but also meaningful integration into financial decision-making processes (Suri & Jack, 2016).

Empirical evidence demonstrates a correlation between financial inclusion and greater household resilience to economic and climate shocks (Chhatre et al., 2023; Zetterli, 2023). Resilience improves when households or individuals can access formal savings, credit, and insurance products, which are efficiently delivered through digital platforms. In rural Indian contexts, digital financial access supports smoother consumption smoothing and investment in adaptive measures (Chhatre et al., 2023). Digital tools play a crucial role in financing climate adaptation, particularly in resource-constrained environments (Zetterli, 2023).

Gender inequalities are deeply embedded in digital financial inclusion metrics. Evidence from multiple Indian states shows that women are less likely than men to own digital finan-

cial accounts, indicating a persistent gender gap. This disparity reflects entrenched constraints, including traditional gender roles, limited autonomy, and unequal access to technology, all of which restrict women's participation in the digital financial ecosystem (Duvendack et al., 2023). Gupta and Kiran further highlight these barriers' multifaceted nature, noting lower digital literacy rates among women, constrained access to smartphones, and social norms that restrict women's mobility and technology usage (Gupta & Kiran, 2024b). These inequalities not only limit women's direct financial empowerment but also weaken household resilience by curtailing the participation of a critical group in financial decision-making.

The rural–urban divide similarly shapes access and utilization patterns differently. Rural households face infrastructure challenges, such as unreliable electricity, poor network coverage, and socioeconomic barriers, which reduce their ability to engage with digital finance (Gupta & Kiran, 2024b). These infrastructural differences result in spatially uneven benefits from digital financial expansion, necessitating a nuanced understanding of heterogeneity in digital participation and its consequences (Banerjee et al., 2013; Copestake et al., 2025).

Most earlier studies use conventional econometric methods to examine the determinants of digital financial inclusion and resilience. These approaches typically rely on parametric assumptions, linear relationships, and aggregate effects that limit their ability to determine complex nonlinear interactions and subgroup-specific differences. Machine learning applications allow for flexible, high-dimensional analysis capable of capturing intricate relationships in large survey datasets (Chen & Guestrin, 2016; Lundberg & Lee, 2017).

However, machine learning models are generally focused on predictive accuracy, rather than population inference. Interpretable machine learning methods, particularly game theory–based SHapley Additive exPlanations (SHAP) and causal forest analysis, address this limitation by providing interpretable, additive decompositions of feature contributions while preserving predictive accuracy (Lundberg & Lee, 2017).

Taken together, based on the available literature, three key conclusions can be drawn. First, there has been significant growth of digital payment systems in developing economies like India. Second, even though there is expansion, there remain persistent spatial inequalities across gender, income, and education due to multiple factors, such as infrastructural and behavioral barriers. Third, most of the existing empirical studies use conventional econometric methods and rely on the assumption of aggregate and linear relationships. This approach limits the ability to capture the non-linear and complex synergies and subgroup-specific heterogeneity. Thus, a clear gap emerged in how digital readiness translates into actual payment adoption across the heterogeneous population groups. To address this gap, we adopted a flexible, data-driven approach capable of identifying distributional impacts of UPI readiness beyond its average impact.

Under this backdrop, the present study aims to examine the heterogeneous effects of UPI readiness on digital payment adoption in India. Specifically, the study aims to examine the following hypotheses:

- H1: *UPI readiness has a positive effect on individual-level digital payment adoption.*
- H2: *The effects of UPI readiness on digital payment adoption vary across socioeconomic and demographic groups, including income, education, gender, and urban–rural location.*
- H3: *The marginal effects of UPI readiness on the adoption of digital payments are greater for those with more structural and digital access constraints than for those who are relatively advantaged.*

2. METHODS

This study uses microdata from the World Bank's *Global Findex Database 2025: Connectivity and Financial Inclusion in the Digital Economy* (World Bank, 2025). The survey provides detailed individual-level information on financial inclusion indicators, access to digital technologies, and exposure to socioeconomic and climate-related shocks. The

analysis focuses exclusively on the Indian sample, which is composed of 3,000 individuals sampled across all major states, using a stratified multistage sampling design to ensure representativeness at the national and regional levels. Survey-provided sampling weights are applied to adjust for the sampling design and nonresponse biases, thereby enabling unbiased population-level inference.

We construct a digital payment index using multiple survey indicators to measure individual-level engagement with digital financial services. The specific indicators include the use of mobile phones or cards for household cleaning supplies (*fin25e1*) and in-store purchases (*fin25e2*); the frequency of digital in-store merchant payments (*fin25e3*), scaled from weekly to less than monthly; the use of mobile phones or computers for bill payments (*fin26a*); and the stated reasons for exclusive cash use (*fin25e4*), which are reverse-coded to indicate the absence of payment barriers. After these items are recoded as binary or scaled variables, the normalized components are averaged to produce a composite index that captures the breadth and frequency of digital payment use, yielding a bounded index variable ranging from 0 to 1 (Suri & Jack, 2016; World Bank, 2021).

The predictor variables are selected to capture different dimensions of digital connectivity and financial inclusion, barriers to access, experiences of natural disasters, saving behaviors, and key sociodemographic characteristics. UPI readiness is operationalized as a binary indicator equal to one if an individual jointly owns a formal financial account and a smartphone, and zero otherwise. Table 1 presents all explanatory variables included in the model, grouped by conceptual domain.

The latent barrier indices are constructed from multiple survey items that reflect common obstacles faced by individuals. These obstacles include affordability constraints, limitations in physical access, concerns regarding privacy and security, and challenges related to digital literacy and usability. Using principal component analysis (PCA), two latent factors are derived, each representing a separate dimension of digital access barriers.

Binary variables are coded consistently, and categorical variables with multiple levels are recoded into meaningful ordinal or nominal forms to support interpretable analysis. PCA is used to

Table 1. Description of key variables, including measurement types and coding schemes

Source: Author's calculations based on secondary data.

Category	Variable/ Construct	Description/Measurement	Type/Coding
Digital Connectivity	Device ownership	Type of phone owned: none, basic, smartphone	Ordinal categorical (0-2)
	Internet use frequency	"Never," "Infrequent," or "Frequent" use	Ordinal categorical
	Account ownership	Bank, financial, mobile, digital account ownership	Binary (0/1)
Barriers to Access	Latent barrier factor 1	Financial and usability barriers (basic phone)	PCA-derived factor
	Latent barrier factor 2	Affordability and usability barriers (smartphone)	PCA-derived factor
Natural Disaster Experience	fin24c	Experienced natural disaster/severe weather	Binary (0/1)
	fin24d1	Lost income or unable to work due to a disaster	Binary (0/1)
	fin24d2	Damage to the home or livestock	Binary (0/1)
	fin24d3	Could not access/use financial account	Binary (0/1)
Saving Behavior	fin17a	Saved formally (bank/institution)	Binary (0/1)
	fin17c	Saved informally (savings club/person)	Binary (0/1)
Sociodemographic Controls	Gender (female)	Female = 1, male = 0	Binary
	Urban residence	Urban = 1, rural = 0	Binary
	Education attainment	Primary or less, secondary, tertiary+	Ordinal categorical
	Age	Age of respondent	Continuous
	Employment status	Currently employed	Binary (0/1)
	Income quintiles	Income level quintile	Ordinal categorical (1-5)

synthesize multiple barrier indicators into two principal components representing phone and smartphone access constraints, with explained variances of 58% and 61%, respectively. Outliers are examined and retained because they plausibly reflect vulnerable populations captured in economic survey data. All continuous variables are scaled to standardized units where appropriate to support model convergence and interpretability.

After the construction of the variables, the multi-layer analysis has been performed in a systematic manner. First, Extreme Gradient Boosting (XGBoost) is used as a weighted regressor to incorporate survey weights and thereby ensure unbiased population-level inference. Hyperparameters, including maximum tree depth, learning rate, subsample ratio, sample-by-tree ratio, number of estimators, and L2 regularization, are tuned through a grid search combined with 5-fold cross-validation of the training sample to optimize predictive accuracy and prevent overfitting.

Second, SHAP is applied to estimate the importance and direction of each explanatory variable's contribution to the continuous target variable. SHAP provides consistent and additive attribution of feature-level contributions for individual predictions (Lundberg & Lee, 2017). To examine expected differences in digital payment adoption, SHAP contrast analyses are conducted by computing mean SHAP values stratified by gender, urban–rural residence, educational attainment, and income quintiles. These contrasts identify disparities in digital resilience pathways without imposing parametric assumptions. Third, an unsupervised K-means clustering algorithm is applied to the high-dimensional SHAP value matrix. The optimal number of clusters is identified through silhouette analysis. The resulting clusters are profiled according to their characteristic SHAP signatures, demographic composition, and resilience scores, enabling policy-relevant segmentation for designing targeted interventions tailored to groups facing distinct digital-financial barriers and opportunities. Finally, the causal forest method is used to quantify the heterogeneous treatment effects of UPI readiness on digital payment adoption.

3. RESULTS

3.1. Descriptive analysis of digital payment usage

The weighted digital payment usage index averages 0.34 with a standard deviation of 0.28. It also spans the full range from minimal engagement to extensive use across multiple payment modes. This suggests substantial variation in digital adoption within the population. The index distribution is right-skewed, with 50% of respondents scoring at or below 0.156. This pattern reflects a bimodal distribution characterized by a large group of no adopters and a distinct group of intensive users.

3.2. Demographic heterogeneity in digital payment usage

The survey estimates show substantially greater digital payment intensity for men than for women in the surveyed population, with weighted means of 0.375 (SD = 0.295) for men versus 0.269 (SD = 0.217) for women. This difference highlights persistent barriers limiting women's active use of digital financial services, despite increased account ownership resulting from targeted government programs such as Pradhan Mantri Jan Dhan Yojana (PMJDY). Multiple factors, such as lower smartphone ownership, digital literacy constraints, sociocultural norms restricting mobility and access, and concerns around trust and security, can be attributed to this lower engagement of women with the digital payment system.

Urban–rural divides are also prominent, with urban respondents having higher weighted index scores (0.382, SD = 0.297) than their rural counterparts (0.295, SD = 0.244). Rural areas, comprising 68% of the weighted sample, dominate low-usage tiers, where more than 75% of the scores are below 0.467.

Income quantiles further intensify inequities. Across quintiles, weighted means increase from 0.248 (Q1) to 0.452 (Q5). The 75th percentile of the top quintile reaches 0.800. By contrast, the uniform clustering of Q1 is near the minimum. Employment status reveals a natural advantage for those in the labor force: employed individuals score 0.345 (weighted mean) against 0.288 for in-

dividuals not employed in the labor force. The age distributions are balanced (weighted mean: 36.6 years, $SD = 15.6$), with younger cohorts (under 35 years) obtaining higher scores through their technological affinity, which is consistent with RBI's youth-led UPI surge (85% of users under 40; RBI, 2024).

3.3. Enabling and constraining factors

Although internet access is the most critical enabler of digital payment usage, 54.5% (weighted) of surveyed individuals report never using the internet, 39.4% use it daily, and the remaining 6.2% are infrequent users. Limited access directly constrains digital payment engagement because 90% of high-index users are daily internet users.

The survey data also show that 25.7% (weighted) of individuals experienced natural disasters in the past 3 years, with severe impacts such as income loss (17.1%), home damage (15.4%), and financial account inaccessibility (9.9%). Saving behaviors remain dominated by informal mechanisms, with only 23.8% (weighted) of individuals saving formally (*fin17a*) compared with 13.1% saving through clubs (*fin17c*).

3.4. XGBoost model performance

The predictive performance of the weighted XGBoost regression model demonstrates strong explanatory power and generalizability. The training set yields a root mean squared error (RMSE) of 0.134 and a coefficient of determination (R^2) of 0.743. When evaluated on the held-out test set, the RMSE increases modestly to 0.168, and the R^2 decreases to 0.596. This indicates some reduction in performance with unseen data while still maintaining satisfactory predictive accuracy.

3.5. Feature importance and SHAP analysis

SHAP analysis (Figure 1) identifies mobile account ownership (*account_mob*), formal financial account access (*account_fin*), and digital account ownership (*dig_account*) as the most influential predictors of digital payment adoption. The strong overlap among these account-based predictors indicates the strategic importance of expanding ac-

cess to both digital and formal financial platforms to increase digital payment usage.

Income quintile (*inc_q*), internet use frequency (*con26_ord*), and educational attainment (*educ_ord*) also emerge as consistently significant correlates, with higher-income individuals, more frequent internet users, and more highly educated individuals achieving higher digital payment index scores.

Notably, *barrierscore_1* and *barrierscore_2*, which capture affordability and usability challenges associated with basic phones and smartphones, respectively, exhibit negative SHAP impacts. This pattern aligns with studies showing that barriers to effective digital engagement extend well beyond device ownership and include cost-related constraints, limited digital literacy, and operational challenges that materially hinder digital financial inclusion. Sociodemographic controls such as gender (*female*), age, and urban–rural residence (*urban_bin*) also contribute to heterogeneity in digital payment behavior. Men, urban residents, and younger individuals tend to be more active users. However, these variables have relatively lower predictive power.

3.6. SHAP dependence plot

The SHAP dependence plots are shown in Figure 2. These plots show the marginal effects of key predictors on the digital payment index along with their possible interacting covariates. The color gradients indicate heterogeneity in these relationships across relevant interacting variables. The analysis reveals the following patterns:

1. Mobile account ownership (*account_mob*), formal financial account (*account_fin*), and digital account ownership (*dig_account*): The dependence plots (Figure 2a–c) for these variables show a clear positive monotonic relationship, with individuals who possess active accounts displaying substantially higher SHAP values. This pattern indicates a strong conditional effect on predicted digital payment intensity.
2. Income Quintile (*inc_q*), Education (*educ_ord*), and Urban Residence (*urban_bin*): The

Source: Author's estimate based on secondary data.

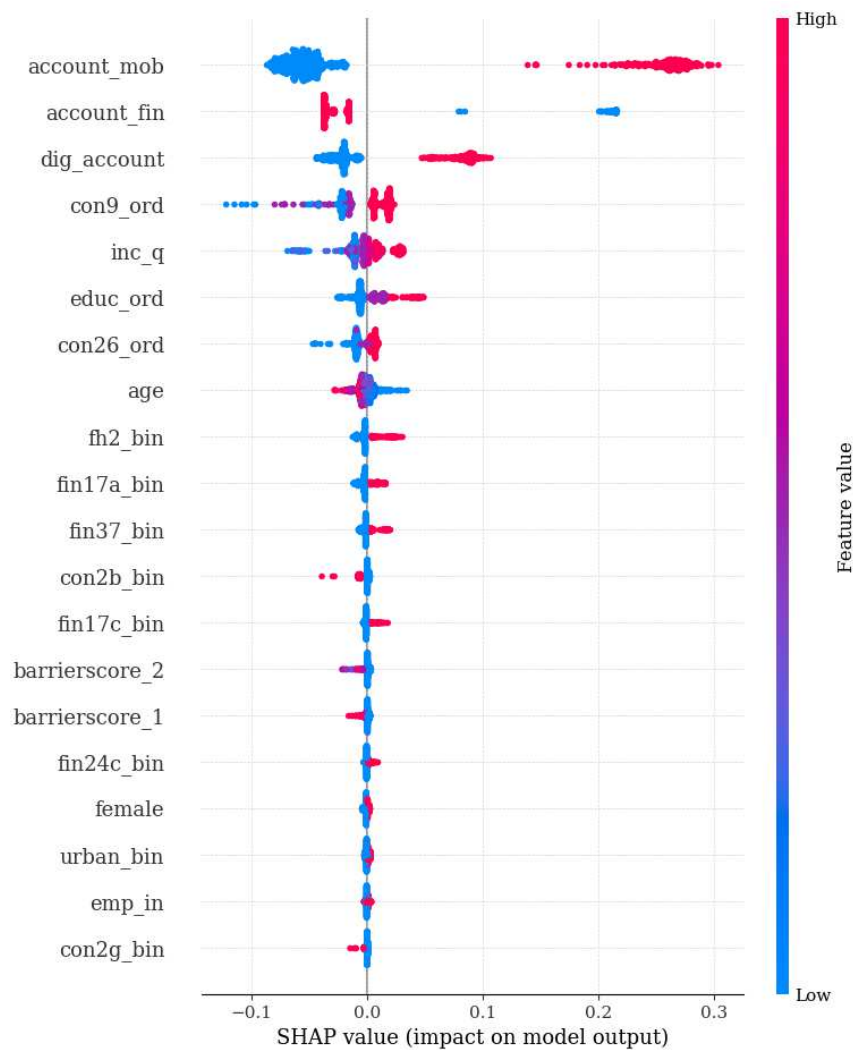


Figure 1. SHAP summary dot plot

plots for income and education (Figure 2e, f–i) show clear stratification, with higher education and higher income levels associated with stronger positive SHAP impacts. These patterns indicate that socioeconomic status amplifies digital payment engagement, likely reflecting greater affordability, higher digital literacy levels, and stronger supporting infrastructure in urban areas. Together, these factors contribute to spatial disparities characteristic of India's digital divide.

3. Barrier scores (*barrierscore_1*, *barrierscore_2*): A marked negative association is also evident among individuals who face greater usability and affordability barriers to phone and smartphone ownership, with higher barrier values producing progressively lower SHAP impacts (Figure 2k–l). These patterns highlight the
4. Gender (*female_bin*) and Age (*age*): The dependence plots for gender and age (Figure 2h–j) show moderate but consistent effects, with

underlying structural constraints on digital inclusion and suggest that targeted efforts to mitigate these barriers could substantially increase adoption among marginalized groups. Notably, the effects are not uniform; instead, they interact strongly with mobile account ownership (*account_mob*). While higher usability and affordability barriers reduce digital payment engagement for all users, this negative effect is considerably weaker among individuals who hold an active mobile account. Mobile account ownership, therefore, not only facilitates digital payment participation directly but also moderates the detrimental impact of structural barriers.

male and younger respondents generally exhibiting higher SHAP values.

5. Secondary features and interactions: A notable feature of the SHAP dependence analysis is that, for almost all predictors, the most salient interaction effects occur with variables that measure financial inclusivity, particularly the different forms of account ownership (e.g., mobile accounts, digital accounts, and formal bank accounts) and digital access through smartphones and the internet. This is evident in the plots, where the color gradients representing interaction effects are predominantly linked to the presence or absence of these account-based and digital access variables.

3.7. SHAP contrasts for gender and urbanicity

The mean SHAP values for major features across different socioeconomic groups (income quintiles, education, gender, and place of residence (rural or urban)) are reported in Tables 2 to 5. These contrasts show that the marginal effect of mobile account ownership (*account_mob*) on the digital payment index is most pronounced among high-income, tertiary-educated, male, and urban populations, highlighting entrenched digital divides and structural advantages. In comparison, the influence of formal financial account ownership (*account_fin*) is more evenly distributed, although it still benefits relatively privileged groups.

Source: Author's estimate based on secondary data.

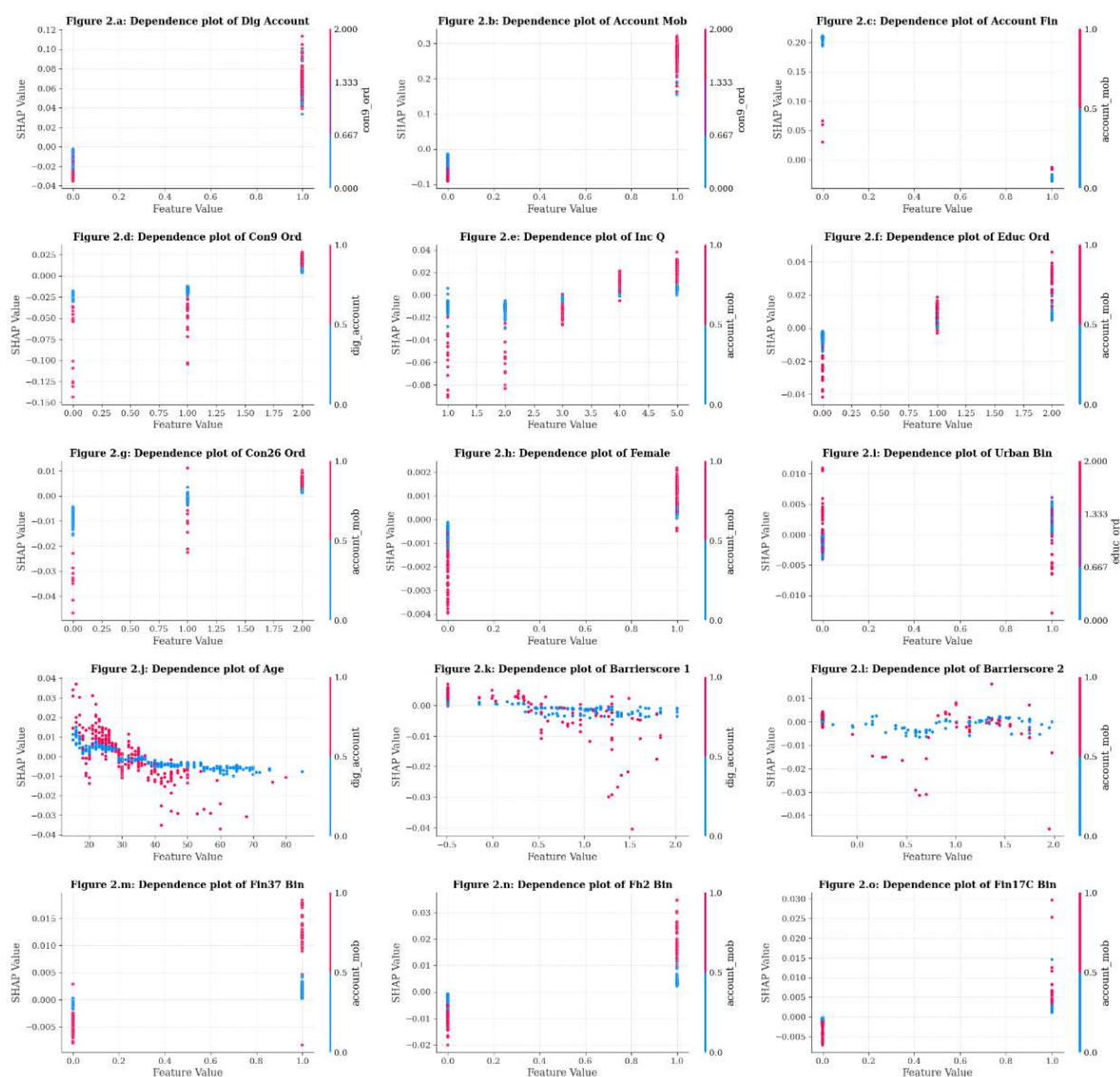


Figure 2. SHAP dependence plot

Digital account ownership (*dig_account*), educational attainment (*educ_ord*), and income quintile (*inc_q*) similarly exhibit wider SHAP dispersion among advantaged populations. By contrast, the SHAP values for affordability and usability barriers related to smartphones (*barrierscore_2*) are higher among urban and more educated groups,

indicating persistent latent constraints even within high-connectivity populations. Overall, these contrasts show that digital payment engagement and the factors that facilitate it vary substantially across sociodemographic groups and, therefore, support the case for targeted approaches to digital financial inclusion policy.

Table 2. SHAP value dispersion by income quintile

Source: Author's estimate based on secondary data.

Feature	Q1	Q2	Q3	Q4	Q5	Dispersion
account_mob	0.0689	0.0629	0.0842	0.1299	0.1681	0.1052
dig_account	0.0289	0.0299	0.0358	0.0486	0.0609	0.0321
account_fin	0.0632	0.0538	0.0511	0.0442	0.0369	0.0263
educ_ord	0.0069	0.0069	0.0089	0.0131	0.0142	0.0074
fh2_bin	0.0041	0.0039	0.0039	0.005	0.0079	0.004
fin17a_bin	0.0031	0.0029	0.0033	0.0054	0.0067	0.0038
con9_ord	0.0182	0.0182	0.0183	0.0196	0.0215	0.0033
fin37_bin	0.0026	0.0023	0.0026	0.0038	0.0044	0.0021
barrierscore_2	0.0009	0.0011	0.0013	0.0013	0.0027	0.0018
age	0.0059	0.0052	0.0054	0.0052	0.0069	0.0017

Table 3. SHAP value dispersion by education level

Source: Author's estimate based on secondary data.

Feature	Primary	Secondary	Tertiary	Dispersion
account_mob	0.0725	0.1643	0.2014	0.129
dig_account	0.0293	0.0641	0.0754	0.0461
account_fin	0.0586	0.0321	0.0267	0.0319
inc_q	0.0093	0.0178	0.0191	0.0098
fh2_bin	0.0036	0.0079	0.0086	0.005
fin17a_bin	0.0032	0.0067	0.0071	0.0039
age	0.0049	0.008	0.0043	0.0037
fin37_bin	0.0022	0.0051	0.0057	0.0036
con9_ord	0.0184	0.021	0.02	0.0026
barrierscore_2	0.001	0.0025	0.0027	0.0017

Table 4. SHAP value dispersion by gender

Source: Author's estimate based on secondary data.

Feature	Female	Male	Dispersion
account_mob	0.0832	0.1253	0.0422
dig_account	0.0336	0.0489	0.0153
account_fin	0.0532	0.0459	0.0072
inc_q	0.01	0.0142	0.0043
educ_ord	0.0085	0.0117	0.0032
con9_ord	0.0204	0.0181	0.0023
fh2_bin	0.0039	0.0061	0.0022
age	0.0048	0.0066	0.0018
fin17a_bin	0.0036	0.0052	0.0016
con2b_bin	0.0031	0.0018	0.0014

Table 5. SHAP value dispersion by urban–rural residence status

Source: Author's estimate based on secondary data.

Feature	Urban	Rural	Dispersion
account_mob	0.0954	0.1266	0.0312
account_fin	0.0458	0.0575	0.0117
dig_account	0.0391	0.0469	0.0078
educ_ord	0.0095	0.0116	0.0021
fh2_bin	0.0047	0.0058	0.0011
fin17a_bin	0.0041	0.0051	0.0011
con2b_bin	0.0026	0.002	0.0006
con26_ord	0.0077	0.0083	0.0006
age	0.0059	0.0054	0.0005
female	0.0008	0.0012	0.0004

3.8. SHAP-based clustering

We employ a model-aware clustering framework by applying K-means clustering to the SHAP values. Unlike traditional clustering based on raw attributes, this approach groups individuals according to the similarity of feature contributions within the predictive model. This way, the k-means clustering identifies latent behavioral and socioeconomic profiles that shape model outcomes. This ensures that the resulting clusters differ not only in their input characteristics but also in how those

characteristics affect the model's predictions, improving interpretability and policy relevance. The optimal number of clusters was determined using the Silhouette score across a range of solutions (2–10), and the results are presented in Table 6. The K-means clustering with the optimal three clusters is estimated, and Figure 3 reports the SHAP contribution of each feature for each cluster.

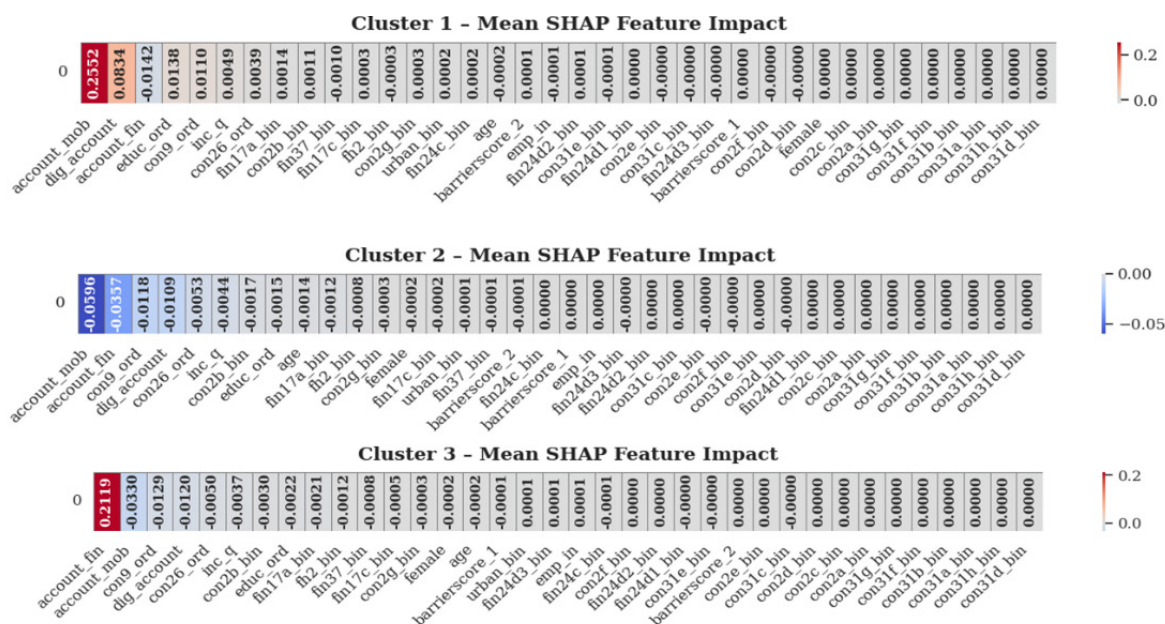
By examining the SHAP contribution of each explanatory variable, cluster profiling is performed as follows:

Table 6. Silhouette scores for the optimum cluster size

Source: Author's estimate based on secondary data.

Number of Clusters (k)	2	3	4	5	6	7	8	9	10
Silhouette Score	0.7409	0.8030	0.7076	0.7007	0.6598	0.3258	0.5505	0.4453	0.3639

Source: Author's estimate based on secondary data.

**Figure 3.** Mean SHAP feature impact for all clusters

Cluster 1: Mobile Account Driven, Digitally Enabled. This cluster shows the strongest positive mean SHAP impact for mobile account ownership ($account_mob \approx 0.23$), indicating that membership in this segment is closely associated with holding an active mobile financial account. Digital account ownership ($dig_account \approx 0.08$) and formal financial account access ($account_fin \approx 0.07$) act as secondary positive contributors, supported by smaller contributions from higher educational attainment ($educ_ord \approx 0.04$) and income ($inc_q \approx 0.04$). Barrier scores and demographic controls contribute minimally. Overall, this cluster represents individuals whose digital payment engagement is driven primarily by mobile account access and strengthened further by digital-specific accounts and educational or economic advantages.

Cluster 2: Structurally Excluded, Negatively Impacted. This cluster is characterized by strong negative mean SHAP impacts for the three key account types – mobile account ownership ($account_mob \approx -0.06$), digital account ownership ($dig_account \approx -0.02$), and formal financial account access ($account_fin \approx -0.02$). Almost all other fea-

tures, including education, income, barrier scores, and demographic controls, have slightly negative or negligible effects. This profile corresponds to individuals systematically excluded from the digital payments ecosystem, with the absence of account access being the primary driver of their low digital payment index scores. These individuals face deep structural disadvantages and are likely to require foundational interventions in account provision and digital infrastructure before other enabling factors can become influential.

Cluster 3: Financial Account Dominant, Legacy Inclusion. This cluster exhibits the strongest positive mean SHAP impact for formal financial account access ($account_fin \approx 0.21$), followed by mobile account ownership ($account_mob \approx 0.13$) and digital account ownership ($dig_account \approx 0.07$). In contrast to Cluster 1, the defining feature here is reliance on traditional financial account provision rather than digital-first access. Education, income, and other variables contribute minimally. This cluster represents “legacy-included” individuals whose digital payment engagement is grounded primarily in established formal banking infra-

Source: Author's estimate based on secondary data.

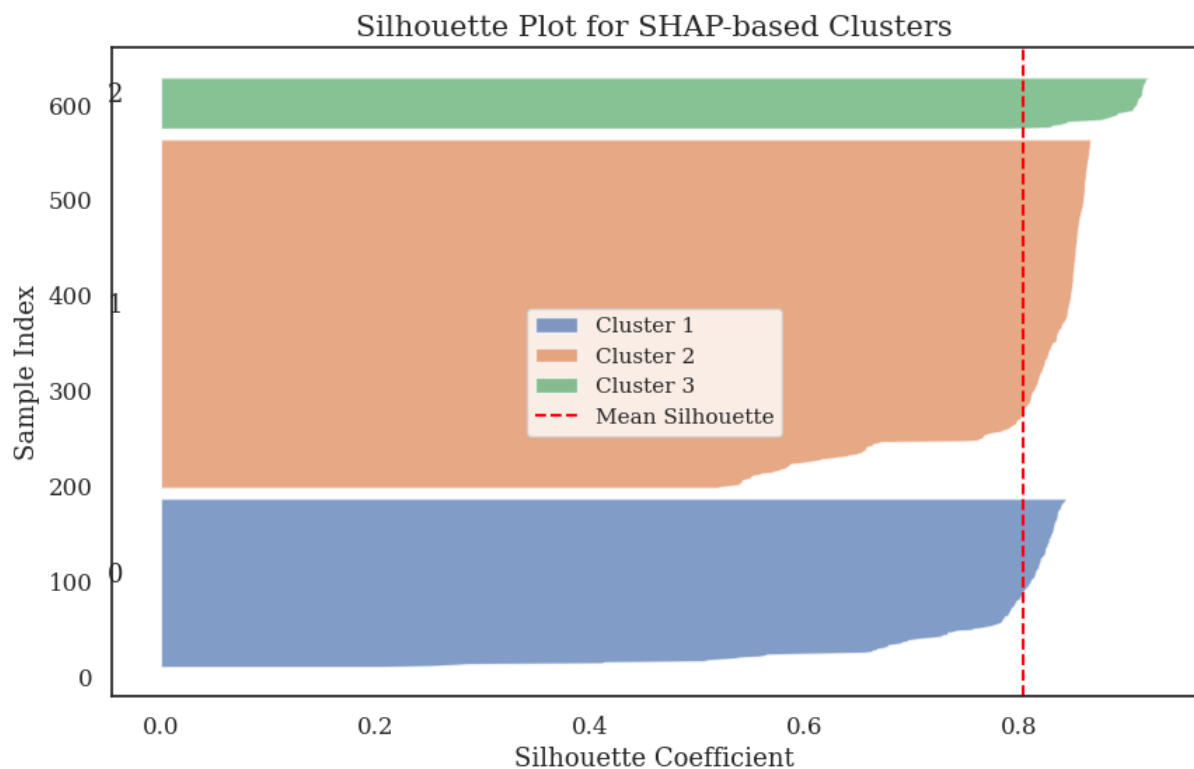


Figure 4. Cluster validation through silhouette scores

structure, with digital and mobile channels serving as important but secondary enablers. Broadly, this cluster aligns with the majority of UPI users.

3.9. Cluster validation and stability

The silhouette analysis demonstrates clear and well-separated cluster structures, with an average silhouette coefficient exceeding 0.8 (Figure 4). This indicates the robustness of the segmentation approach and validates the effectiveness of SHAP-based clustering in capturing meaningful behavioural patterns. The strong cluster separation reflects sufficient homogeneity within clusters and clear heterogeneity across clusters, supporting both the interpretability and the stability of the results.

3.10. Causal forest analysis

We extend the analysis using causal forest models to estimate heterogeneous treatment effects on digital payment behaviors, focusing on individuals' UPI readiness. For this purpose, an individual is defined as 'UPI ready' if they have a formal financial account and own a smartphone. The causal forest model estimates the conditional average treatment effect (CATE) of being 'UPI ready' on the '*digital_pay_index*', identifying how the treatment effect varies across individuals according to demographic, income, educational, locational, and financial exclusion characteristics.

The average treatment effect (ATE) of UPI readiness on the digital payment index is 0.161 (SE = 0.224) on the scale of 0-1. This indicates that concurrent access to a formal financial account and a smartphone increases predicted digital payment engagement by approximately 16 percentage points. Although this average effect is modest relative to its standard error, substantial heterogeneity is evident across population subgroups. The gains are unevenly distributed, concentrated among more advantaged groups and weaker or nonsignificant among others.

By gender, the treatment effects are essentially identical: 0.157 for men and 0.155 for women, and so there is no gender-based disparity in the marginal benefit of UPI readiness. This pattern contrasts with narratives of persistent female exclu-

sion and is likely linked to government-led digital welfare initiatives and female-focused digital literacy campaigns that have reduced gender gaps in responsiveness. A pronounced urban-rural divide persists. Urban residents gain 0.249 units from UPI readiness, more than twice the rural gain of 0.113 units. This spatial disparity reflects rural infrastructure constraints, weaker network coverage, lower merchant acceptance of digital payments, and limited digital ecosystem complementarities. Collectively, these factors reduce the value of acquiring account and device access in rural areas, whereas urban environments benefit from more favorable conditions on all these dimensions.

By education, the treatment effects stratify sharply. Individuals with primary education or less realize a CATE of 0.066, whereas those with secondary education achieve 0.349, a 5.3-fold increase. Tertiary-educated respondents reach a CATE of 0.327, slightly below the secondary-educated group, which may reflect a saturation point where highly educated populations are already engaged intensively with digital payments regardless of treatment. The comparatively low effect among those with primary or no schooling highlights a digital literacy threshold: secondary education provides the computational and digital navigation skills necessary for consistent digital payment use.

The income gradient is even more pronounced. Treatment effects increase monotonically across all income quintiles, with the highest quintile experiencing an effect that is 6.2 times larger than that of the lowest. This pattern indicates how affordability constraints and the presence of complementary digital ecosystem elements concentrate the benefits of UPI readiness among economically advantaged groups.

A key novel finding emerges when examining heterogeneity along the digital device capability barrier index, constructed from affordability and usability barrier scores. This index reveals an inclusion-exclusion spectrum in which the CATE increases monotonically from the most included (least constrained) to the most excluded (most constrained) populations (Figure 5). The most included decile (D1) records a CATE of 0.084, whereas the most excluded decile (D10) reaches 0.308, representing a 3.7-fold increase. This coun-

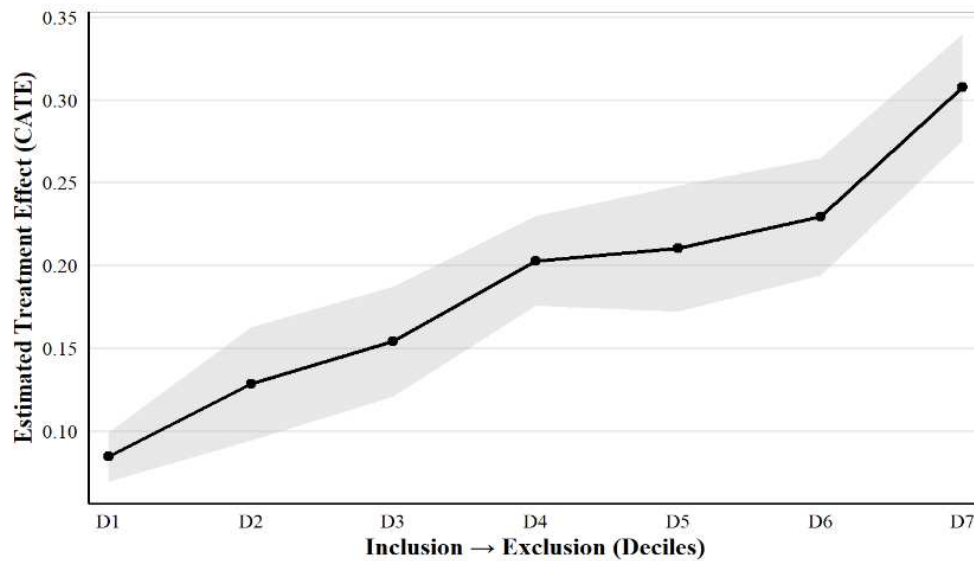


Figure 5. Effect of UPI readiness across the inclusion-exclusion spectrum

terintuitive pattern, where greater structural disadvantage corresponds to larger treatment effects, reflects several reinforcing mechanisms.

Several mechanisms help explain this pattern. First, complementarity and scarcity premiums: for individuals who are highly excluded, gaining both a smartphone and a formal financial account simultaneously resolves multiple resource constraints, creating synergistic multiplier effects that do not accrue to already resourced individuals. Second, baseline deprivation dynamics: individuals starting from very low levels of digital engagement experience proportionally larger relative gains when constraints are relaxed. Third, selection effects: within the excluded population, those who achieve treatment are likely a positively selected subset – more motivated or better positioned to adopt digital systems – and, therefore, use these resources more intensively. Fourth, threshold nonlinearities: digital payment adoption depends on critical affordability and infrastructure thresholds; crossing these thresholds triggers accelerated adoption for excluded groups, whereas already included groups have long surpassed these limits. Finally, policy amplification: India's direct benefit transfer architecture channels government welfare payments directly into formal accounts, providing strong incentives for excluded individuals to adopt and intensify digital payment use once access is secured, whereas these incentives are already embedded for those who are included.

We also estimate intersection effects, focusing on gender–residence combinations:

- 1) urban men (n = 509, CATE = 0.243);
- 2) urban women (n = 450, CATE = 0.255);
- 3) rural men (n = 1,015, CATE = 0.115); and
- 4) rural women (n = 1,023, CATE = 0.112).

Urban women experience a slightly larger effect than urban men (0.255 vs. 0.243), suggesting that government digital welfare programs and female-focused interventions have partially offset other disadvantages in urban settings. By contrast, rural women face a dual disadvantage: rural treatment effects are already restricted by weaker infrastructure, and female-specific barriers produce the lowest combined effect (0.112). These patterns highlight the importance of spatially and gender-sensitive policy strategies.

All estimates are validated using 500 bootstrap replications, confirming the stability of the results. Subgroup sample sizes are adequate (minimum n = 307 in decile 1), and treatment positivity assumptions are met. The increasing CATE pattern across the inclusion-exclusion spectrum remains robust to alternative constructions of the barrier index and to different sample stratifications, indicating that the observed heterogeneity reflects genuine effects instead of statistical artefacts.

Table 7. CATE of UPI readiness by sociodemographic and socioeconomic characteristics

Source: Author's estimate based on secondary data.

Stratification	Subgroup	N	CATE (SE)	95% CI
Income Quintile	Q1 (Lowest)	645	0.067 (0.041)	[-0.013, 0.147]
	Q2	612	0.082 (0.038)	[0.008, 0.156]
	Q3	598	0.091 (0.035)	[0.022, 0.160]
	Q4	702	0.124 (0.033)	[0.059, 0.189]
	Q5 (Highest)	540	0.414 (0.052)	[0.312, 0.516]
Education Level	Primary or Less	1,247	0.066 (0.029)	[0.009, 0.123]
	Secondary	1,652	0.349 (0.044)	[0.263, 0.435]
	Tertiary or more	598	0.327 (0.051)	[0.227, 0.427]
Urban–Rural	Urban	1,289	0.249 (0.039)	[0.173, 0.325]
	Rural	2,208	0.113 (0.032)	[0.050, 0.176]
Gender	Male	1,639	0.157 (0.035)	[0.088, 0.226]
	Female	1,858	0.155 (0.033)	[0.090, 0.220]
Gender x Residence	Urban Male	509	0.243 (0.052)	[0.141, 0.345]
	Urban Female	450	0.255 (0.055)	[0.147, 0.363]
	Rural Male	1,015	0.115 (0.041)	[0.035, 0.195]
	Rural Female	1,023	0.112 (0.038)	[0.037, 0.187]

Table 8. CATE of UPI readiness by inclusion-exclusion spectrum

Source: Author's estimate based on secondary data.

Decile	Inclusion Category	N	CATE (SE)	95% CI
D1	Most Included	307	0.084 (0.041)	[0.005, 0.163]
D2		361	0.128 (0.039)	[0.052, 0.204]
D3		372	0.154 (0.036)	[0.084, 0.224]
D4		369	0.203 (0.045)	[0.115, 0.291]
D5		375	0.210 (0.047)	[0.118, 0.302]
D6	Middle	356	0.229 (0.049)	[0.133, 0.325]
D7		359	0.268 (0.051)	[0.168, 0.368]
D8		368	0.287 (0.053)	[0.183, 0.391]
D9		341	0.295 (0.055)	[0.187, 0.403]
D10	Most Excluded	307	0.308 (0.062)	[0.187, 0.429]

4. DISCUSSION

The descriptive estimates show that one-third of the adults use digital payment. This estimate is closely aligned with national estimates reported by the RBI and NPCI (RBI, 2024). This alignment reinforces longstanding evidence of India's digital divide, where regional, socioeconomic, and demographic disparities persist despite rapid UPI expansion and PMJDY-driven improvements in financial inclusion (ICRIER, 2024).

The gender disparities in our data remain pronounced, with men exhibiting substantially higher digital payment intensity than women. Although some studies report narrowing gaps or localized cases of female-led adoption (Ansar et al., 2021; Duvendack et al., 2023), our findings align more closely with research that highlights persistent

structural constraints faced by women, particularly limited access to devices, affordability barriers, and restrictions on mobility (Gupta & Kiran, 2024). These patterns suggest that, despite gender-targeted digital literacy programs increasing engagement, the underlying barriers remain influential.

Spatial rural–urban divides in our estimates also mirror the RBI's finding that urban areas dominate digital transaction volumes despite representing a smaller share of the population (RBI, 2024). Previous studies attribute these differences to broadband scarcity, weaker telecommunications networks, and inconsistent digital infrastructure across rural regions (Laskar, 2023; Sindakis & Showkat, 2024). Our results reinforce the extent to which these infrastructural asymmetries continue to shape individual-level digital payment behaviors.

Income- and employment-linked disparities in our data are also consistent with the broader digital finance diffusion literature. Higher-income and employed individuals show systematically greater engagement with digital payments, reflecting affordability constraints, liquidity insecurity, and increased risk perceptions among lower-income households (Asif et al., 2023; Jacob et al., 2024). Younger respondents, consistent with demographic analyses, display stronger adoption, reinforcing evidence of youth-driven UPI expansion (Hasan et al., 2024; RBI, 2024).

The machine learning results reinforce and extend these patterns. SHAP-based interpretability identifies account ownership combined with reliable digital access as the strongest predictor of digital payment uptake. This finding is consistent with peer-reviewed research emphasizing the complementarity between traditional financial inclusion and digital infrastructure (Thanigan et al., 2025; Tiwari et al., 2019). The consistency between machine learning-based attribution and earlier econometric evidence points to a robust behavioral mechanism: digital access is necessary but remains insufficient without foundational financial inclusion.

Most empirical studies on digital payments in India conceptualize inclusion in binary terms, either digitally included or excluded, with adoption typically modelled as a yes-no outcome. Large-scale National Sample Survey Office and National Family Health Survey analyses similarly empha-

size the divide between users and nonusers, often attributing adoption patterns to income, education, device access, and demographic characteristics (Asif et al., 2023; ICRIER, 2024). Behavioral studies also tend to position individuals along a single continuum of adoption intensity rather than identifying structurally distinct pathways (Hasan et al., 2024). In contrast, our analysis identifies three distinct user segments: digitally enabled and mobile account-driven; structurally excluded and adversely affected; and financially included through legacy account ownership. This three-way segmentation moves beyond the conventional “adopters vs. non-adopters” framework commonly used in Indian digital finance research and provides a more granular understanding of heterogeneous digital payment trajectories.

The causal forest analysis offers new insights into the heterogeneous impacts of UPI readiness. Although the average treatment effects are modest, the gains are substantially larger for rural, low-income, and low-literacy users. These patterns align with wider evidence showing that digital interventions often generate the greatest marginal benefits for structurally constrained groups once access barriers are reduced. A notable finding is the near-equal marginal gains for men and women, suggesting that gender-focused initiatives have reduced differences in responsiveness, even though gaps in overall adoption persist. Our results, therefore, extend current evidence by demonstrating that digitally enabling underserved groups can produce disproportionately large behavioral shifts.

CONCLUSIONS

This study examines the impact of Unified Payments Interface (UPI) readiness on digital payment adoption and the heterogeneity present in India using nationally representative microdata and machine learning methods. The results show that owning a smartphone, a formal account, or a digital account increases digital payment by approximately 0.161 on a 0-1 scale, with substantially larger gains – up to 3.7 times the average – among the most excluded subgroups. These amplified effects reflect synergies such as policy-driven incentives and threshold-based nonlinearities. Intersectional patterns, including greater gains for urban women than for urban men, highlight the importance of combined disadvantages in shaping resilience to shocks. These effects are shaped by a range of barriers, including affordability and usability constraints, as well as differences linked to income, education, gender, and urban–rural location. The SHAP analysis further highlights important nonlinearities and interaction patterns. For instance, account ownership increases adoption most strongly among urban and higher-income groups, whereas rural and female respondents experience more pronounced negative influences from affordability and usability barriers.

SHAP-based clustering identifies three population groups:

- 1) digitally enabled users who rely primarily on mobile accounts;
- 2) structurally excluded individuals with limited account ownership and weak digital access; and
- 3) legacy users anchored in traditional financial accounts who nevertheless participate in the UPI ecosystem.

These clusters reveal distinct pathways to digital engagement. Taken together, the results show that UPI readiness exerts highly heterogeneous effects on digital payment adoption. The most significant gains occur among individuals facing the greatest affordability and usability constraints, indicating that targeted policies to expand smartphone ownership and formal account access among rural, low-income, and less-educated groups could deliver the most meaningful improvements in digital financial inclusion and help reduce India's persistent digital divides.

To promote equitable digital payment adoption, policies should address specific barriers and target particular population segments:

- Addressing the exclusion group (Cluster 2): Prioritize basic access by subsidizing smartphones and expanding rural internet coverage, particularly in areas with less than 45% connectivity. Link these efforts to mobile account openings through programs such as the PMJDY, with targeted emphasis on women, who exhibit disproportionately large treatment gains in excluded groups.
- Enhancing usage (Clusters 1 and 3): Provide incentives such as fee waivers for frequent UPI transactions and offer training programs to help legacy banking users transition to digital modes. In urban areas, support women-led initiatives to strengthen engagement and build on their relatively higher marginal gains.
- Reducing broader gaps: Incorporate digital literacy measures into national surveys and employ analytical tools such as SHAP for continuous monitoring of disparities. Develop shock-responsive features, including UPI-based microinsurance products, to enhance financial resilience, with potential adoption gains of 15%-20%, as projected by the World Bank (2023).
- Policies should focus on the affordability and usability barriers faced by the most excluded populations, as these groups experience the largest marginal benefits from UPI readiness.

AUTHOR CONTRIBUTIONS

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Supervision: Bidyut Kumar Ghosh.

Validation: Bidyut Kumar Ghosh.

Visualization: Bidyut Kumar Ghosh.

Writing – original draft: Bidyut Kumar Ghosh.

Writing – reviewing & editing: Bidyut Kumar Ghosh.

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