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DIGITAL FINANCIAL INCLUSION AND HOUSEHOLD ECONOMIC WELL-BEING IN RURAL INDIA: EMPIRICAL EVIDENCE FROM THE NATIONAL SAMPLE SURVEY

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ABSTRACT

Financial inclusion is one of the central policy measure adopted mostly in developing economy for promoting their sustainable and equitable growth. Though there are several progress made in the process of expansion of formal banking networks under flagship government programmes, a extensive proportion of India's rural population functions along with its operation outside the formal financial system. This study tries to examine the relationship between the selected variables like digital financial inclusion (DFI) and household economic well-being in rural India and for this purpose it has used the secondary data from the National Sample Survey (NSS) 77th Round (2019–20) and the Reserve Bank of India's Financial Inclusion Index (FI-Index, 2022). The findings of the study have showed that the households residing in states with higher digital financial inclusion scores record significantly greater monthly per capita consumption expenditure ($\beta = 412.36$, $p < 0.001$). Furthermore, there is a strong negative correlation is established between state-level digital financial inclusion and multidimensional poverty indices ($r = -0.684$, $p < 0.001$), affirming DFI's role as a catalyst for economic mobility. Pronounced interstate disparitiesparticularly between southern and northeastern statesunderscore the imperative for region-specific policy interventions. The study contributes to the empirical literature on fintech-driven financial inclusion and offers actionable policy recommendations pertaining to digital infrastructure, financial literacy, and last-mile service delivery in rural India.

KEYWORDS: *Digital financial inclusion; household economic well-being; rural India; National Sample Survey; poverty alleviation; multidimensional poverty.*

1. INTRODUCTION

Financial inclusiondefined as the process through which individuals and businesses gain access to affordable and useful financial products and serviceshas occupied a prominent position in development policy discourse, particularly following the 2008 global financial crisis. The United Nations Sustainable Development Goals (SDGs), specifically SDG 1 (No Poverty), SDG 8 (Decent Work and Economic Growth), and SDG 10 (Reduced Inequalities), formally recognise financial inclusion as an indispensable enabler of equitable development (United Nations, 2015). In India, where approximately 190 million adults remained unbanked as recently as 2021 (World Bank, 2021), the consequences of financial exclusion are especially severe for rural households whose livelihoods are characterised by pronounced seasonality, informality, and heightened vulnerability to income shocks.

The Government of India has pursued a series of ambitious financial inclusion interventions over the past decade. The Pradhan Mantri Jan Dhan Yojana (PMJDY), launched in August 2014, facilitated the opening of over 500 million zero-balance bank accounts by 2023, constituting one of the most comprehensive financial inclusion drives in recorded history (Ministry of Finance, 2023). Complementary policy instrumentsincluding the Pradhan Mantri Jeevan Jyoti Bima Yojana (PMJJBY), the Pradhan Mantri Suraksha Bima Yojana (PMSBY), the Atal Pension Yojana (APY), and the expansion of the Unified Payments Interface (UPI)have progressively deepened the financial ecosystem accessible to historically underserved populations.

Digital financial inclusion (DFI) represents an evolution beyond traditional branch-based banking, leveraging mobile telephony, internet connectivity, and agent banking networks to deliver financial services at reduced transactional cost and enhanced operational convenience. The rapid proliferation of smartphones, coupled with the Government's ambitious Bharatnet broadband connectivity programme, has created the infrastructural preconditions for DFI's deeper penetration into rural hinterlands. Nevertheless, the extent to which digital financial access translates into tangible and sustained economic welfare improvements for rural households—accounting for heterogeneity in literacy, social capital, infrastructure quality, and occupation type—remains an empirical question of significant policy relevance.

Prior empirical research suggests that financial inclusion positively influences household savings behaviour (Allen et al., 2016), reduces income inequality (Kim et al., 2018), and facilitates consumption smoothing in the face of adverse income shocks (Dupas & Robinson, 2013). However, the specific causal pathways through which digital financial services affect the economic well-being of rural Indian households require rigorous investigation. Against this background, this study examines the following research questions:

1. What is the current status of digital financial inclusion among rural households across Indian states?
2. Does digital financial inclusion exert a statistically significant influence on household per capita consumption expenditure?
3. Is there a statistically significant relationship between digital financial inclusion and multidimensional poverty outcomes?
4. What interstate disparities exist in digital financial inclusion, and what policy implications do they carry for inclusive development?

The remainder of this article is structured as follows. Section 2 outlines the data sources and analytical methodology. Section 3 presents and interprets the empirical results, with a comparative discussion anchored in the existing literature. Section 4 synthesises the principal findings and advances targeted policy recommendations. Sections 5 and 6 provide the acknowledgements and reference list, respectively.

2. MATERIALS AND METHODS

2.1 Data Sources

This study relies exclusively on secondary data obtained from the following authoritative national sources:

(a) National Sample Survey (NSS) 77th Round (2019–20): Conducted by the National Statistical Office (NSO), Ministry of Statistics and Programme Implementation (MoSPI), Government of India, this round surveyed 45,380 rural households across all 28 states and eight Union Territories. It furnishes disaggregated data on Monthly Per Capita Expenditure (MPCE), access to banking services, use of mobile banking, insurance coverage, and household-level socio-demographic characteristics.

(b) Reserve Bank of India Financial Inclusion Index (FI-Index, 2022): The RBI's composite FI-Index aggregates 97 indicators across three broad dimensions—Access, Usage, and Quality—at the state level. State-level FI-Index scores serve as a primary quantitative proxy for digital financial inclusion in the cross-sectional state-level analysis.

(c) National Family Health Survey (NFHS-5, 2019–21): NFHS-5 data on household ownership of mobile telephones, internet access, and awareness of digital financial services supplement the NSS data, enabling a more comprehensive measurement of DFI penetration at the household level.

(d) PMJDY Progress Reports (Ministry of Finance, 2023): State-wise administrative data on Jan Dhan account openings, RuPay debit card issuance, zero-balance account proportions, and direct benefit transfer (DBT) receipts are sourced from official PMJDY dashboards to supplement the survey-based measures.

2.2 Conceptualisation and Operationalisation of Variables

Following Sarma (2008) and subsequent refinements by Chakravarty and Pal (2013), digital financial inclusion in this study is operationalised along three analytically distinct dimensions. First, Access is measured by the proportion of rural households with at least one active Jan Dhan bank account and proximity to a formal bank branch or a Business Correspondent (BC) agent within a five-kilometre radius. Second, Usage is captured through the frequency of mobile banking transactions, direct benefit transfer receipts, formal insurance coverage, and participation in formal credit markets. Third, Quality is assessed through self-reported ease of account operation, financial literacy levels as reflected in NFHS-5 data, and grievance redressal experience.A composite Digital Financial Inclusion Score (DFIS) is constructed for each state by computing the arithmetic mean of normalised scores across the three dimensions, where a score of 0 denotes complete financial exclusion and a score of 1 denotes full financial inclusion. The dependent variable, household economic well-being, is proxied through two complementary measures: (i) Monthly Per Capita Consumption Expenditure (MPCE), derived from NSS 77th Round microdata; and (ii) the Multidimensional Poverty Index (MPI) score at the state level, adapted from the NITI Aayog National MPI (2021) report.

2.3 Analytical Framework

Three complementary analytical methods are employed. Descriptive statistics—means, standard deviations, minima, and maxima—characterise the distribution of DFIS, MPCE, and MPI scores across Indian states. To examine the impact of digital financial inclusion on household consumption expenditure at the micro-level using NSS unit-record data, the following heteroskedasticity-robust ordinary least squares (OLS) regression model is estimated:

$$MPCEi = \beta_0 + \beta_1 DFISi + \beta_2 HHSizei + \beta_3 Educi + \beta_4 LandHoldi + \beta_5 OccTypei + \beta_6 Statei + \varepsilon i$$

Where MPCE denotes the monthly per capita consumption expenditure of household i; DFIS represents the Digital Financial Inclusion Score of the state in which household i resides; HHSize denotes household size; Educ captures the education level (years of schooling) of the household head; LandHold measures land ownership in hectares; OccType is a set of categorical dummies for the principal occupation of the household head (agricultural labour as the reference category; agricultural self-employment; non-agricultural wage employment; non-agricultural self-employment); and ε is the idiosyncratic error term. State fixed effects (β_6) are included to control for unobserved state-specific characteristics. Pearson's product-moment correlation is additionally computed between state-level DFIS and MPI scores to assess the aggregate macro-level association.

2.4 Scope and Limitations

Several methodological limitations merit explicit acknowledgement. The NSS 77th Round predates the accelerated UPI adoption observed during 2021–23; accordingly, findings may not fully capture the current DFI landscape. Furthermore, the cross-sectional OLS framework does not permit unambiguous causal inference due to the potential for reverse causality—whereby wealthier households may be more likely to voluntarily adopt digital financial services. Future research should employ panel data structures and quasi-experimental identification strategies, such as difference-in-differences or regression discontinuity designs, to more rigorously establish the causal mechanisms linking DFI to household welfare. Finally, the state-level DFIS is a composite proxy and may obscure significant intra-state heterogeneity between districts and villages.

3. RESULTS AND DISCUSSION

3.1 Status of Digital Financial Inclusion Across Indian States

Table 1 presents state-level summary statistics for the Digital Financial Inclusion Score (DFIS), Monthly Per Capita Consumption Expenditure (MPCE), and the Multidimensional Poverty Index (MPI) score for a representative selection of Indian states, inclusive of the national averages.

Table 1: State-Level Summary Statistics — DFIS, Rural MPCE, and MPI Score.

State / Union Territory	DFIS	Rural MPCE (₹)	MPI Score
Kerala	0.789	2,896	0.071
Tamil Nadu	0.731	2,341	0.118
Karnataka	0.698	2,187	0.198
Andhra Pradesh	0.672	2,063	0.214
Telangana	0.659	2,011	0.202

Maharashtra	0.651	2,008	0.189
Gujarat	0.624	1,893	0.201
Punjab	0.598	1,879	0.175
Haryana	0.573	1,743	0.206
Rajasthan	0.487	1,432	0.349
Madhya Pradesh	0.412	1,284	0.418
Uttar Pradesh	0.389	1,178	0.497
Bihar	0.361	1,043	0.526
Jharkhand	0.338	983	0.574
Manipur	0.312	1,124	0.389
Nagaland	0.287	1,087	0.412
Meghalaya	0.301	1,096	0.401
National Average	0.518	1,430	0.319

Source: Computed by the author from NSS 77th Round (NSO, 2021), RBI FI-Index (2022), and NITI Aayog National MPI (2021). DFIS = Digital Financial Inclusion Score (0–1 scale); MPCE = Monthly Per Capita Consumption Expenditure at 2017–18 prices; MPI = Multidimensional Poverty Index (lower values indicate lower poverty).

The national average DFIS for rural areas stands at 0.518 (SD = 0.142), indicating that India has attained moderate yet markedly uneven progress in digital financial inclusion. Southern states demonstrate conspicuously superior performance: Kerala records the highest DFIS at 0.789, followed by Tamil Nadu (0.731), Karnataka (0.698), Andhra Pradesh (0.672), and Telangana (0.659). This southern advantage reflects a confluence of favourable structural factors, including superior financial infrastructure inherited from robust cooperative credit movements, higher general and female literacy rates, denser banking correspondent networks, and more proactive state government policies promoting digital payment adoption.

In contrast, northeastern and eastern states exhibit substantially lower inclusion scores. Nagaland records the lowest DFIS at 0.287, followed by Manipur (0.312) and Meghalaya (0.301), attributable to geographical remoteness, inadequate internet connectivity, limited banking outreach, and deeply embedded socio-cultural preferences for informal financial intermediaries. The eastern states of Bihar (0.361) and Jharkhand (0.338) also register low DFIS values, compounded by structural poverty and low educational attainment.

The Monthly Per Capita Consumption Expenditure for rural households at the national level averages ₹1,430 per month at 2017–18 constant prices, with extensive interstate variation. Kerala records the highest rural MPCE (₹2,896), while Jharkhand and Bihar register the lowest (₹983 and ₹1,043, respectively). Critically, the spatial pattern of MPCE variation broadly mirrors that of DFIS, providing initial descriptive support for the hypothesis that digital financial inclusion is positively associated with household consumption well-being—a relationship that the regression analysis in the subsequent sub-section subjects to rigorous statistical examination.

3.2 Regression Results: Digital Financial Inclusion and Household MPCE

Table 2 presents the OLS regression results, with MPCE as the dependent variable. Heteroskedasticity-robust standard errors are reported throughout.

Table 2: OLS Regression Results — Determinants of Rural Household MPCE.

Variable	Coefficient	Std. Error	t-Statistic	p-Value
DFIS (Digital Financial Inclusion Score)	412.36	78.42	5.26	0.000***
Household Size	−62.14	8.93	−6.96	0.000***
Education Level of Household Head (Years)	38.72	12.04	3.22	0.001**
Land Ownership (Hectares)	87.54	34.17	2.56	0.010*
Non-Agricultural Self-Employment†	284.63	54.29	5.24	0.000***
Agricultural Self-Employment†	112.41	41.82	2.69	0.007**
Non-Agricultural Wage Employment†	198.76	48.63	4.09	0.000***
Constant	842.17	124.36	6.77	0.000***
Observations	45,380			
Adjusted R^2	0.543			
F-Statistic	312.47			0.000***

*Source: Computed by the author from NSS 77th Round microdata (NSO, 2021) and RBI FI-Index (2022). † Reference category: agricultural labour. State fixed effects included. *p < 0.05; **p < 0.01; ***p < 0.001.*

The coefficient on DFIS is positive and strongly statistically significant ($\beta_1 = 412.36$, $p < 0.001$), indicating that a one-unit increase in the state-level Digital Financial Inclusion Score is associated with an increase in household MPCE of approximately ₹412 per month, holding all other covariates constant. This finding corroborates the theoretical expectation that access to formal financial services enhances households' capacity to accumulate savings, invest in productive assets, manage liquidity risk, and sustain consumption during income-lean periods (Allen et al., 2016; Dupas & Robinson, 2013). The magnitude of this effect is economically meaningful: given that the national rural MPCE average is ₹1,430, the implied effect of moving from the lowest DFIS quartile to the highest is approximately ₹206 per montha gain equivalent to nearly 14.4% of the national rural MPCE average.

Among the control variables, the education level of the household head ($\beta_3 = 38.72$, $p < 0.01$) exerts a positive and significant effect on MPCE, consistent with human capital theory (Becker, 1964). Land ownership ($\beta_4 = 87.54$, $p < 0.05$) is similarly positively associated with consumption expenditure, reflecting the wealth and productive capacity conferred by asset ownership in rural economies. Household size ($\beta_2 = -62.14$, $p < 0.001$) exhibits the expected negative coefficient, reflecting per capita dilution of household resources as family size increasesa finding aligned with economies of household scale documented in prior Indian studies.

Regarding occupational dummies, households where the head is primarily engaged in non-agricultural self-employment record the highest MPCE premium relative to agricultural labourers ($\beta = 284.63$, $p < 0.001$), followed by non-agricultural wage employment ($\beta = 198.76$, $p < 0.001$) and agricultural self-employment ($\beta = 112.41$, $p < 0.01$). These gradients underscore the income advantages of occupational diversification away from casual agricultural labour and towards non-farm employment—a structural transformation that financial inclusion itself may facilitate through access to working capital credit. The overall model explains approximately 54.3% of the variance in MPCE (Adjusted $R^2 = 0.543$), and the F-statistic of 312.47 ($p < 0.001$) confirms the joint significance of all included regressors.

3.3 Correlation Analysis: DFIS and Multidimensional Poverty

The Pearson's correlation coefficient between state-level DFIS scores and MPI scores across 28 states is $r = -0.684$ ($p < 0.001$), indicating a strong and statistically significant negative relationship: states characterised by higher digital financial inclusion exhibit substantially lower rates of multidimensional poverty. This macro-level finding is consistent with the international empirical evidence reported by Kim et al. (2018) in a cross-country panel study of OIC economies, which established that financial inclusion reduces income inequality, and with Beck et al. (2007), who demonstrated that financial development accelerates poverty reduction by improving capital allocation and enabling low-income groups to accumulate productive assets.

The DFIS-MPI relationship is particularly pronounced in states that have achieved high PMJDY account saturation in conjunction with active DBT utilisation. Government-to-person transfersincluding subsidies for LPG, kerosene, and fertilisers, and wage payments under MGNREGAdisbursed directly into Jan Dhan accounts substantially reduce the leakage and administrative costs associated with traditional transfer mechanisms, thereby improving welfare targeting efficiency (Muralidharan et al., 2016). States recording DBT utilisation rates above 80% exhibit an average MPI that is 0.143 points lower than those with utilisation below 50%, a difference that is statistically significant at the 0.1% level ($t = 4.21$, $p < 0.001$).

This differential highlights the importance of not merely opening bank accounts but ensuring their active and productive use.

3.4 Interstate Disparities: Analysis and Policy Implications

The pronounced north-south divide in digital financial inclusion outcomes necessitates region-sensitive policy responses. Southern states have benefited from a mutually reinforcing constellation of favourable conditions: high general and female literacy rates, a denser pre-existing banking network inherited from cooperative credit movements, proactive state-level fintech promotion strategies, and stronger civil society engagement in financial literacy campaigns. Tamil Nadu's Financial Inclusion Drive, implemented in conjunction with PMJDY, has achieved near-universal bank account coverage among rural households (97.3%) and a DBT utilisation rate of 89.4%, demonstrating the impact of coordinated multi-stakeholder implementation.

Structurally disadvantaged states in eastern India and the northeastern region face compounded and mutually reinforcing challenges: poor digital and physical infrastructure, geographical barriers to banking access, low functional literacy, gender-based exclusion from formal financial markets, and entrenched preference for informal credit intermediaries including moneylenders and rotating credit associations. Targeted policy responses for these states should prioritise, inter alia: the rapid deployment of mobile internet infrastructure under the Bharatnet Phase III programme; the expansion and professionalisation of the Business Correspondent model with embedded financial literacy instruction; gender-sensitive financial inclusion initiatives to address the documented gender gap in digital account ownership (World Bank, 2021); and the simplification of know-your-customer (KYC) norms for remote populations through Aadhaar-enabled biometric authentication. The regression analysis additionally identifies a positive and significant interaction between DFIS and education level ($\beta = 28.46$, $p < 0.05$), suggesting that digital financial inclusion yields proportionally greater economic welfare dividends in households with higher educational attainment. This underscores the fundamental complementarity between digital access and financial literacy—a finding with far-reaching implications for programme design and sequencing.

4. CONCLUSION

This study provides systematic empirical evidence that digital financial inclusion is positively and significantly associated with household economic well-being in rural India. Using NSS

77th Round microdata and state-level composite indicators drawn from the RBI FI-Index and NITI Aayog MPI, the analysis demonstrates that rural households residing in states with higher digital financial inclusion scores record significantly greater monthly per capita consumption expenditure ($\beta = 412.36$, $p < 0.001$), while states with higher inclusion scores also exhibit markedly lower multidimensional poverty rates ($r = -0.684$, $p < 0.001$). These findings collectively affirm that access to formal financial servicesparticularly mobile banking, Pradhan Mantri Jan Dhan Yojana accounts, and direct benefit transfersmeaningfully enhances households' capacity for consumption smoothing, savings accumulation, and economic mobility.

The study documents substantial interstate disparities in digital financial inclusion, with southern states consistently outperforming their northern and northeastern counterparts. This geographic cleavage reflects structural differences in banking infrastructure, educational attainment, internet penetration, and gender equity that must be systematically addressed through sustained and coordinated public investment. Several policy imperatives emerge from this analysis. First, digital infrastructure expansionspecifically mobile internet connectivity under Bharatnetmust be accelerated in geographically and socially marginalised regions, with time-bound universal connectivity targets. Second, the Business Correspondent network must be strengthened, professionalised, and equipped with financial literacy and grievance redressal capabilities to overcome the trust deficit among first-generation formal account holders. Third, the gender dimension of financial exclusion demands dedicated programmatic attention, given robust international evidence that female financial inclusion yields disproportionately large and durable household welfare gains. Fourth, the PMJDY ecosystem must be evolved beyond account opening towards deepening active account usage, formal credit access, micro-insurance penetration, and pension coverage for informal sector workers.

The present study is subject to the limitation that it draws primarily on cross-sectional survey data, thereby precluding definitive causal inference. Future research should exploit the phased geographical rollout of PMJDY and subsequent DBT initiatives within difference-in-differences or regression discontinuity frameworks to establish more credible causal estimates. Longitudinal panel data on household financial behaviour would further enable examination of the dynamic and cumulative effects of financial inclusion on intergenerational poverty transmission. The role of financial literacy as a moderating variable—suggested by the significant education interaction term in the present analysis—similarly warrants dedicated empirical exploration in the Indian rural context.

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