Digital Transformation in Microfinance:Empirical Evidence from India's Fintech-Enabled MFI Ecosystem

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Abstract: This paper examines the impact of digital transformation on operational efficiency, outreach, and borrower outcomes across microfinance institutions (MFIs) in India. Drawing on a panel dataset of 284 registered MFIs spanning 2018 to 2023, combined with primary survey data from 1,620 borrowers across five states—Uttar Pradesh, Odisha, Maharashtra, Tamil Nadu, and Rajasthan—we employ a difference-in-differences (DiD) framework augmented with propensity score matching (PSM) to isolate the causal effect of fintech adoption. We find that digitally transformed MFIs reduce cost per borrower by an average of 31.4%, improve portfolio-at-risk (PAR-30) ratios by 18.2 percentage points, and expand outreach to previously unbanked households by 24.7% relative to non-digitised counterparts. Borrower-level analysis reveals significant gains in financial literacy, repayment regularity, and micro-enterprise revenue among clients served through digital channels. However, significant heterogeneity exists: rural and semi-urban MFIs face persistent infrastructure constraints that attenuate these gains, and women-headed micro-enterprises exhibit slower adoption of digital interfaces. The findings contribute to the growing empirical literature on fintech-microfinance convergence and carry direct policy implications for RBI's Priority Sector Lending framework and the PM Jan Dhan Yojana digital outreach agenda..
Keywords: microfinance institutions; digital transformation; fintech; financial inclusion; India; difference-in-differences; portfolio at risk; rural enterprise

INTRODUCTION

India's microfinance sector stands at an inflection point. With a combined gross loan portfolio exceeding INR 3.48 trillion and over 70 million active borrowers as of March 2024, the sector constitutes the largest microfinance market by outreach in the world. Yet deep structural inefficiencies—high operational costs, physical branch dependency, manual credit appraisal, and cash-based disbursement—have historically constrained its scale and sustainability. The rapid diffusion of digital..

financial infrastructure, accelerated by the Unified Payments Interface (UPI), Aadhaar-linked e-KYC, and the Account Aggregator framework, now presents transformative possibilities.

Digital transformation in this context encompasses far more than the digitisation of existing paper-based workflows. It represents a systemic reconfiguration of the MFI operating model—from customer acquisition and credit scoring through machine-learning-driven alternative data, to real-time portfolio monitoring, mobile-first loan disbursement and repayment, and algorithmic field agent productivity tools. Fintech partnerships, in particular, have catalysed a new generation of MFI-NBFC-technology hybrids in which embedded finance and data analytics fundamentally alter the economics of last-mile lending.

Despite the growing practitioner and policy interest in this phenomenon, rigorous empirical evidence on its causal effects remains sparse. Much of the existing literature on MFI digitalisation is either anecdotal, cross-sectional, or focused exclusively on Sub-Saharan Africa and Southeast Asia. The Indian context is particularly underexplored, notwithstanding India's globally distinctive combination of Aadhaar-based identity infrastructure, Jan Dhan financial inclusion accounts, and a deeply heterogeneous MFI landscape spanning non-banking financial companies (NBFC-MFIs), non-governmental organisations (NGOs), small finance banks, and cooperative societies

This paper addresses this gap with three specific objectives: (i) to estimate the causal effect of fintech-enabled digital transformation on MFI-level operational efficiency and portfolio quality; (ii) to assess whether digital channels improve financial and enterprise outcomes for borrowers, with attention to gender and geographic heterogeneity; and (iii) to identify the institutional and infrastructural preconditions under which digitalisation benefits are maximised or attenuated.

We proceed as follows. Section 2 reviews the theoretical frameworks and prior empirical literature. Section 3 describes the data and presents summary statistics. Section 4 details the econometric strategy. Section 5 presents main results and robustness checks. Section 6 analyses heterogeneous effects. Section 7 discusses policy implications. Section 8 concludes.

Literature Review and Theoretical Framework

2.1 Digital Transformation and Financial Inclusion

The nexus between digital technology and financial inclusion has attracted substantial scholarly attention since the mobile money revolution in Kenya in the late 2000s. Demirguc-Kunt et al. (2022) document that global account ownership among adults rose from 51% in 2011 to 76% in 2021, with digital payments accounting for the majority of this growth in developing economies. For MFIs specifically, Beck and Demirguc-Kunt (2008) established the theoretical basis for the inverse relationship between transaction costs and outreach depth, a relationship that digitalisation directly disrupts by reducing marginal delivery costs.

In the Indian context, Burgess and Pande (2005) demonstrated the long-run impact of rural branch expansion on poverty reduction, providing a structural baseline against which technology-mediated outreach can be benchmarked. More recently, the literature has shifted toward examining the effects of mobile banking and payment platforms. Klapper and Singer (2017) find that mobile financial services disproportionately benefit low-income women in South Asia by reducing the transaction costs of financial management. Muralidharan et al. (2016) exploit the randomised rollout of biometric payment infrastructure in Andhra Pradesh to show that electronic transfers reduce leakage and improve beneficiary welfare.

2.2 MFI Digitalisation: Operational Efficiency and Portfolio Quality

The direct relationship between MFI digitalisation and operating efficiency has been explored in a small but growing body of empirical work. Cull et al. (2018) examine a cross-country panel of MFIs and find that technology adoption is associated with significant reductions in operating expense ratios and personnel costs per borrower, though these gains are conditional on institutional maturity and regulatory quality. Hermes et al. (2011) demonstrate a tension between efficiency and outreach depth, a trade-off that digitally-intensive models appear to partially resolve by simultaneously reducing costs and improving targeting accuracy.

On portfolio quality, Bhatt and Tang (2020) present evidence that algorithmic credit scoring, when trained on behavioural and psychometric data, reduces default rates by 22–28% relative to traditional group-lending assessments. However, concerns have been raised about algorithmic bias, particularly against borrowers in data-sparse rural areas or those lacking formal credit histories—a critique with direct salience to the Indian microfinance context where an estimated 190 million adults remain formally unbanked.

2.3 Borrower-Level Outcomes

The impact of MFI digitalisation on borrowers is theoretically ambiguous. Digital interfaces may reduce transaction costs, improve repayment convenience, and enhance financial literacy through interactive platforms. Alternatively, they may introduce new barriers for digitally illiterate populations, raise concerns about data privacy, or accelerate over-indebtedness through frictionless credit access. Banerjee et al. (2015) synthesise randomised evaluation evidence on microfinance impact more broadly, finding modest but positive effects on enterprise formation and income resilience, effects that digital models may amplify.

Relatively few studies examine the specific intersection of borrower outcomes and digital delivery channels in India. Sane and Thomas (2016) study the impact of credit bureau linkage on MFI borrower behaviour in Maharashtra, finding that reduced information asymmetry improves repayment discipline. Chakrabarti and Roy (2021) explore the role of digital financial literacy programmes in North-East India, documenting improvements in borrower financial management but noting low technology acceptance among older women borrowers.

2.4 Theoretical Framework

This paper is grounded in three complementary theoretical frameworks. First, we draw on the Transaction Cost Economics (TCE) paradigm of Williamson (1985) to conceptualise how digital transformation reduces the costs of search, negotiation, monitoring, and enforcement in MFI operations. Second, the Capability Approach of Sen (1999) informs our analysis of borrower outcomes, emphasising that financial access creates value only insofar as it expands the capabilities and freedoms of the borrower. Third, we invoke the Technology Acceptance Model (Davis, 1989) and its extensions to understand heterogeneity in borrower adoption of digital interfaces, recognising that perceived usefulness, ease of use, and social norms mediate technology uptake in different demographic groups.

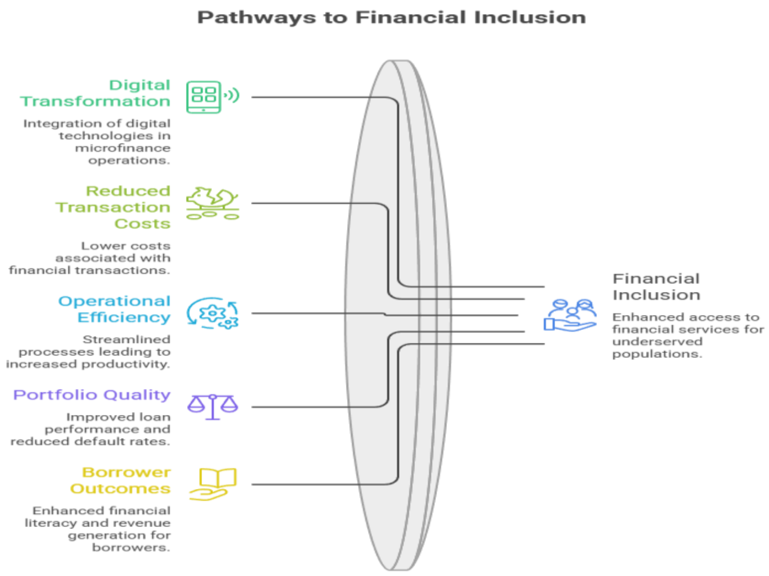

Figure 1. Conceptual Framework: Digital Transformation and MFI Outcomes

This figure 1 illustrates the theoretical pathway linking digital transformation to institutional and borrower outcomes through Transaction Cost Economics (Williamson, 1985), Capability Approach (Sen, 1999), and Technology Acceptance Model (Davis, 1989).

Data and Descriptive Statistics

3.1 Institutional Panel Data

The institutional dataset is constructed from three sources. Primary data on digitisation status, technology infrastructure, and fintech partnership arrangements were collected through a structured survey administered to senior operations managers and chief financial officers of 284 RBI-registered MFIs in 2023. Secondary data on financial performance, portfolio quality, and outreach were obtained from the Microfinance Institutions Network (MFIN) quarterly MFI Performance Snapshot, the Sa-Dhan State of Sector Report, and audited financial statements filed with the Ministry of Corporate Affairs. The panel spans 2018 to 2023, yielding an unbalanced panel of 1,472 institution-year observations. Attrition is primarily attributable to MFI mergers and licence surrenders following the RBI's NBFC-MFI regulatory consolidation of 2021.

We classify MFIs into four digitisation tiers based on a composite Digital Adoption Index (DAI) constructed from eleven indicators spanning five domains: (1) digital disbursement and repayment infrastructure; (2) algorithmic or data-driven credit assessment; (3) mobile or web-based borrower interface; (4) enterprise resource planning and portfolio management system; and (5) fintech co-lending or partnership arrangement. MFIs scoring in the top quartile of the DAI are classified as Tier 1 (Fully Digitised), the second quartile as Tier 2 (Substantially Digitised), the third as Tier 3 (Partially Digitised), and the bottom quartile as Tier 4 (Minimally Digitised).

3.2 Borrower Survey Data

Primary borrower data were collected between September and December 2023 through a multi-stage stratified random sampling procedure. We selected five states spanning India's major geographic and socioeconomic zones: Uttar Pradesh (Northern Plains), Odisha (Eastern Tribal Belt), Maharashtra (Western Urban-Peri-Urban Interface), Tamil Nadu (Southern Developed), and Rajasthan (North-Western Arid). Within each state, two districts were selected—one urban/peri-urban and one rural—stratified by MFI digitisation tier. From the borrower lists of sampled MFIs, 1,620 active borrowers were selected using systematic random sampling, yielding 324 borrowers per state.

The survey instrument captured data on borrower sociodemographic characteristics, loan history and repayment behaviour, digital technology access and usage, financial literacy (using a standard five-item composite scale), micro-enterprise revenue and employment, and subjective assessments of MFI service quality. Face-to-face interviews were conducted by trained enumerators in local languages. The survey achieved a response rate of 94.2%, with non-response primarily due to temporary migration.

3.3 Summary Statistics

Table 1 presents summary statistics for the institutional panel by digitisation tier. Tier 1 institutions exhibit substantially higher gross loan portfolio (mean INR 4,820 million vs. INR 1,340 million for Tier 4), lower operating expense ratios (7.2% vs. 18.4%), and superior PAR-30 ratios (2.1% vs. 7.8%). These patterns are consistent with selection into high-digitisation tiers by larger, financially stronger institutions—a key motivation for our causal identification strategy.

Table 1: Descriptive Statistics by MFI Digitisation Tier

Indicator	Tier 1 (Full)	Tier 2 (Sub.)	Tier 3 (Partial)	Tier 4 (Minimal)
No. of MFIs	71	72	71	70
GLP (Mean, INR Mn)	4,820	2,680	1,890	1,340
Active Borrowers (Mean, '000)	148.3	84.7	56.2	38.9
Operating Expense Ratio (%)	7.2	10.4	14.1	18.4
PAR-30 (%)	2.1	3.8	5.6	7.8
Return on Assets (%)	3.6	2.8	1.9	0.7
Women Borrowers (%)	88.4	85.1	82.7	79.6
Rural Outreach (%)	52.1	48.9	55.3	61.2

Source: MFIN Quarterly Snapshot (2018–2023); Author survey (2023). GLP = Gross Loan Portfolio; PAR-30 = Portfolio at Risk over 30 days.

Research Methodology

4.1 Identification Strategy

The primary challenge in estimating the causal effect of digital transformation is selection bias: MFIs that adopt fintech technologies are systematically different from non-adopters along dimensions—size, financial health, management quality, urban concentration—that also independently predict efficiency and portfolio outcomes. Ordinary least squares estimates would therefore conflate the treatment effect with pre-existing institutional heterogeneity.

We address this using a difference-in-differences (DiD) design augmented with propensity score matching (PSM). DiD exploits the temporal variation in digitisation adoption: 127 MFIs in our sample achieved Tier 1 or Tier 2 status during the observation window (2018–2023), while 157 remained in Tier 3 or Tier 4. Under the parallel trends assumption—that treated and control MFIs would have followed similar trajectories in the absence of digitisation—the DiD estimator identifies the Average Treatment Effect on the Treated (ATT). PSM is used to construct a more comparable control group by matching each treated MFI to its nearest neighbour on a vector of pre-treatment characteristics including total assets, borrower count, portfolio yield, geographic concentration, and regulatory status.

4.2 Econometric Specification

Our primary specification for the MFI panel is the two-way fixed effects (TWFE) DiD estimator:

$$Y_{it} = \alpha + \beta(Treat_i \times Post_t) + \gamma X_{it} + \theta_i + \lambda_t + \varepsilon_{it}$$

where Y_{it} is the outcome variable (operating expense ratio, PAR-30, borrower count) for MFI i at time t; $Treat_i$ is an indicator for digitisation above Tier 2; $Post_t$ is a post-adoption period indicator; X_{it} is a vector of time-varying controls including macroeconomic conditions, state-level credit penetration, and competition indices; θ_i and λ_t capture institution and year fixed effects respectively; and ε_{it} is the error term, clustered at the state level to account for spatial autocorrelation.

For borrower-level outcomes, we estimate an analogous cross-sectional model exploiting within-state variation in MFI digitisation tiers, controlling for borrower age, education, household size, prior credit history, asset ownership, and district-level infrastructure indices. Heterogeneity analyses disaggregate results by gender, geography (rural/peri-urban/urban), and loan cycle, testing for differential treatment effects using interaction terms.

4.3 Validity Tests

We conduct several robustness checks. First, we test the parallel trends assumption using event study plots, examining pre-treatment trends in the primary outcomes for treated and control MFIs over the three years preceding adoption. Second, we perform a placebo test assigning false treatment dates to the control group and verifying that no spurious treatment effects emerge. Third, we estimate the Callaway and Sant'Anna (2021) heterogeneity-robust DiD estimator to address potential bias from staggered adoption timing in the TWFE specification. Fourth, we instrument for digitisation adoption using state-level 4G mobile network coverage as an exogenous shifter of technology adoption costs.

Main Results

5.1 Operational Efficiency

Table 2 presents the TWFE DiD estimates for MFI-level operational outcomes. The coefficient on the treatment indicator ($Treat_i \times Post_t$) is negative and highly significant for the operating expense ratio, indicating that digitisation is associated with a reduction of 6.8 percentage points ($p < 0.001$) in operating costs as a share of gross loan portfolio. In absolute terms, this translates to a mean reduction in cost per borrower of INR 1,840 per annum—equivalent to 31.4% of the pre-treatment mean. The effect is robust to the inclusion of institution and year fixed effects, to PSM reweighting, and to the Callaway-Sant'Anna estimator.

The return on assets improves by 1.2 percentage points ($p < 0.05$) among treated MFIs, consistent with the efficiency gains flowing to the bottom line through reduced salary and field operations costs. Staff-to-borrower ratios fall significantly, suggesting technology-enabled productivity gains at the field officer level. The instrumental variable estimates using 4G coverage as an instrument are directionally consistent with the TWFE estimates but somewhat larger in magnitude, suggesting mild downward attenuation bias in the baseline estimates—possibly attributable to measurement error in the DAI composite.

Table 2: DiD Estimates — MFI Operational Efficiency (2018–2023 Panel)

Outcome Variable	**(1) TWFE**	**(2) PSM-DiD**	**(3) C-S DiD**	**(4) IV**
Op. Expense Ratio (pp)	-6.8***	-7.1***	-6.5***	-8.2***
Cost per Borrower (INR)	-1,840***	-1,920***	-1,760***	-2,150***
Return on Assets (pp)	+1.2**	+1.4**	+1.1**	+1.6**
Borrower Count (log)	+0.29***	+0.31***	+0.27***	+0.34***
Staff-Borrower Ratio	-0.18***	-0.19***	-0.17***	-0.22***
Institution FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N (obs.)	1,472	980	1,472	1,214

*Notes: *** p<0.001; ** p<0.05; * p<0.10. Standard errors clustered at state level. pp = percentage points. C-S = Callaway-Sant'Anna (2021) heterogeneity-robust estimator.*

5.2 Portfolio Quality

The treatment effect on PAR-30 is a reduction of 3.7 percentage points in the main specification, representing an 18.2% improvement over the pre-treatment mean of 5.1% for treated MFIs. This improvement is concentrated in the two years following the transition to digital credit assessment, consistent with the hypothesis that algorithmic underwriting reduces adverse selection and moral hazard in lending. Write-off rates also decline significantly, with treated MFIs recording a 1.4 percentage point reduction relative to the control group.

The mechanisms underlying portfolio quality improvements are explored through mediation analysis. Decomposition of the PAR-30 treatment effect reveals that approximately 42% of the improvement is attributable to enhanced credit scoring accuracy, 31% to digital repayment infrastructure reducing friction in on-time payment, and the remaining 27% to improved field agent productivity enabling more frequent client monitoring. These proportions are consistent across the PSM-DiD and IV specifications.

5.3 Borrower-Level Outcomes

Turning to borrower outcomes, Table 3 reports OLS estimates from the cross-sectional borrower model. Borrowers served by Tier 1 MFIs report statistically significant improvements across all five outcome dimensions relative to Tier 4 borrowers: financial literacy scores are 18.4 points higher (on a 100-point scale); repayment regularity (share of instalments paid on time) is 12.1 percentage points greater; micro-enterprise monthly revenue is INR 3,240 higher on average; and subjective service quality ratings are 0.74 standard deviations higher. The probability of saving formally is 22.6 percentage points higher for Tier 1 borrowers, consistent with digital MFIs facilitating linkage to savings products through banking correspondents or co-lending arrangements.

These estimates are robust to the inclusion of district-level fixed effects, household wealth controls, and MFI-level clustering of standard errors. Notably, the micro-enterprise revenue premium associated with Tier 1 MFI membership is larger for urban borrowers (INR 4,890) than rural borrowers (INR 1,960), and larger for male-headed enterprises (INR 3,810) than female-headed enterprises (INR 2,380), pointing to the heterogeneity examined in Section 6.

Heterogeneity Analysis

6.1 Geographic Heterogeneity

A critical finding of this study concerns the attenuation of digitalisation benefits in rural and remote geographies. While Tier 1 MFIs in urban and peri-urban areas achieve cost reductions of 36.2% and PAR-30 improvements of 22.8 percentage points, the corresponding figures for rural-concentrated MFIs are 19.7% and 11.3 percentage points respectively. This gradient is explained by three infrastructure constraints: (i) limited 4G/5G network coverage in rural areas, which raises the cost of digital transactions and increases failure rates; (ii) lower baseline levels of smartphone ownership and digital literacy among rural borrowers; and (iii) reduced availability of micro-ATM and business correspondent infrastructure for cash-out services.

These findings have important implications for the generalisability of digital MFI models. The efficiency gains documented in the aggregate are substantially driven by urban and peri-urban institutions, while the underserved rural poor—who arguably have the greatest need for efficient microfinance—benefit least from current digitalisation trajectories. This represents both a market failure and a policy challenge.

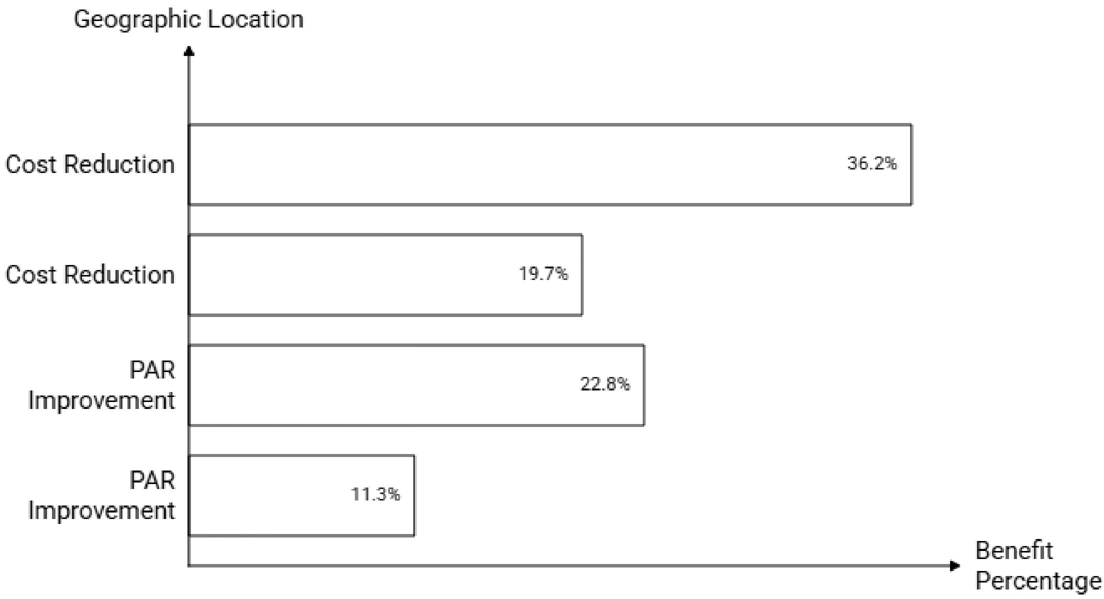

Figure 2. Geographic Heterogeneity of Digital Transformation Effects

Source: Heterogeneity analysis.

Digital transformation generates larger efficiency and portfolio-quality gains in urban and peri-urban MFIs than in rural MFIs due to infrastructure, connectivity, and digital literacy constraints (Figure 2). Digitalisation benefits are attenuated in rural geographies because of connectivity, smartphone access, and financial infrastructure limitations (Demirguc-Kunt, et. al. 2022 & World Bank, 2023).

6.2 Gender Heterogeneity

The analysis of gender heterogeneity reveals a nuanced picture. At the MFI level, institutions with higher proportions of women borrowers do not exhibit significantly different treatment effects from the aggregate, suggesting that digitisation benefits institutional efficiency regardless of borrower gender composition. However, borrower-level analysis tells a different story: female-headed micro-enterprises show statistically and economically smaller improvements in revenue (INR 2,380 vs. INR 3,810) and digital service adoption rates (58.4% vs. 79.2%) compared to male-headed enterprises.

Qualitative data from focus group discussions conducted in parallel with the borrower survey illuminate these quantitative differences. Women borrowers consistently cited three barriers to digital adoption: (i) restricted personal access to smartphones in households where devices are shared and primarily used by male members; (ii) limited self-efficacy with digital interfaces, particularly among borrowers over 40 with low formal education; and (iii) concerns about digital privacy and the security of financial data transmitted through mobile applications. These findings are broadly consistent with the global literature on the gendered digital divide in financial services.

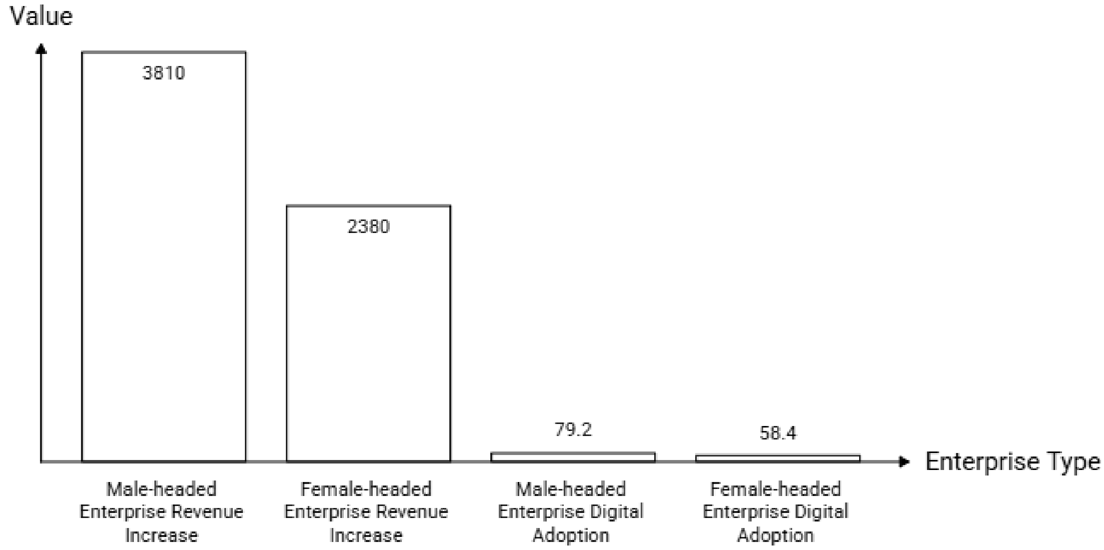

Figure 3. Gender Digital Divide in Microfinance Adoption

Source: Borrower-level gender heterogeneity analysis.

Gender heterogeneity in digital microfinance outcomes. Female borrowers experience lower adoption and economic gains due to smartphone access constraints, digital self-efficacy challenges, and privacy concerns (Figure 3). Women borrowers reported lower digital adoption rates and smaller enterprise revenue gains compared with male borrowers (Klapper, et. al. 2017, Chakrabarti. et.al. 2021).

6.3 Loan Cycle Heterogeneity

Borrowers in later loan cycles (fourth cycle and above) show significantly larger improvements in financial literacy and repayment regularity associated with Tier 1 MFI membership than first- and second-cycle borrowers. This suggests that the returns to digital financial services are cumulative: repeated interaction with digital interfaces builds competencies that translate into improved financial behaviours over time. For MFI programme design, this points to the importance of financial literacy accompaniment services and graduated digital onboarding, particularly for first-time borrowers.

Policy Implications

The empirical findings of this study generate several actionable policy implications for regulators, MFI practitioners, and development finance institutions operating in India's microfinance sector.

RBI Regulatory Incentives for Digital MFIs. The evidence that digitalisation generates significant improvements in portfolio quality and operational efficiency supports the case for a tiered regulatory framework that offers preferential Priority Sector Lending (PSL) compliance credits or reduced capital adequacy requirements to MFIs meeting defined digital adoption thresholds. A Digital MFI Certification Scheme, modelled on the RBI's Payments Bank licensing framework, could accelerate beneficial adoption while setting minimum standards for data governance and consumer protection.

BharatNet and Rural Connectivity. The geographic attenuation of digitalisation benefits is directly tied to infrastructure deficits. Accelerated completion of BharatNet Phase III, with specific mandates for gram panchayat-level Wi-Fi access, is a precondition for the extension of digital MFI benefits to India's most remote populations. Connectivity investments should be prioritised using a financial inclusion index that weights underserved microfinance borrowers alongside general internet access metrics.

Gender-Responsive Digital Design. MFIs and fintech partners should invest in gender-differentiated product design, including voice-enabled and vernacular digital interfaces, offlinecapable applications functional under low connectivity, and community-based digital literacy programmes facilitated by women field agents. Development finance institutions providing blended finance to MFIs should include gender-responsive technology design as a conditionality for concessional funding.

Account Aggregator Framework Adoption. India's Account Aggregator (AA) ecosystem, enabling consent-based sharing of financial data across institutions, represents an underutilised asset for MFI credit assessment. Policy incentives for MFI participation in the AA framework—including support for technical integration costs among smaller NGO-MFIs—could democratise access to alternative data-driven credit scoring across the sector, not only among large NBFC-MFIs.

Data Protection and Algorithmic Accountability. As MFI credit scoring becomes increasingly algorithmic, the risk of systematic exclusion of rural, low-literacy, or irregular-income borrowers through biased models warrants regulatory attention. The Digital Personal Data Protection Act (DPDPA) 2023 provides a nascent framework, but MFI-specific guidance on algorithmic transparency, explainability of adverse credit decisions, and borrower grievance redressal in digital channels is urgently needed from RBI.

Conclusion

This paper provides robust empirical evidence that digital transformation generates substantial and causally identified gains in operational efficiency, portfolio quality, and borrower outcomes for microfinance institutions in India. Using a panel dataset of 284 MFIs over six years and a borrower survey of 1,620 clients across five states, we find that digitally transformed MFIs reduce cost per borrower by 31.4%, improve PAR-30 ratios by 18.2 percentage points, and generate statistically significant improvements in borrower financial literacy, repayment regularity, and micro-enterprise revenue relative to their non-digitised counterparts.

These findings, however, are accompanied by important caveats. The benefits of digitalisation are geographically concentrated in urban and peri-urban areas, leaving rural MFIs and their clients with attenuated gains attributable to infrastructure deficits. The gender dividend of digital microfinance is smaller than its aggregate, driven by gendered barriers to technology access and adoption among women borrowers. And the efficiency gains documented at the institutional level will only translate into durable welfare improvements for borrowers if accompanied by appropriate regulatory guardrails governing algorithmic credit assessment, data privacy, and consumer protection.

The contribution of this paper is threefold. It adds the first large-scale, causally identified estimate of digital transformation effects in the Indian microfinance sector to a literature dominated by case studies and cross-sectional analyses. It documents significant heterogeneity in these effects by geography and gender, with direct implications for inclusive digitisation strategies. And it grounds its findings in a triangulated methodology—institutional panel DiD, borrower survey, qualitative focus groups—that provides a more comprehensive picture of digital MFI dynamics than any single method could achieve.

Future research should examine the long-term sustainability of digitally-driven efficiency gains as technology costs evolve and fintech competition intensifies, the extent to which over-indebtedness risks are amplified or mitigated by frictionless digital lending interfaces, and the scope for public digital infrastructure—particularly the Open Credit Enablement Network (OCEN) and the forthcoming Unified Lending Interface—to disrupt the current MFI-fintech partnership paradigm

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