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Digital Infrastructure as Catalyst for Agricultural Financial Inclusion: South Asian Evidence (2000–2024)

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ABSTRACT

There are still 719 million people living in absolute poverty worldwide, and they account for 64% of the total number of people engaged in agriculture. Based on this, this paper examines whether there is a “threshold effect” in the moderating mechanism of digital infrastructure on the effectiveness of microfinance in alleviating poverty among farmers by employing Dynamic Common Correlated Effects estimation based on panel data of 148 observations from six South Asian countries (2000–2024). We found three key “activation thresholds”: when the proportion of internet users in the population is lower than 8%, microfinance has little effect on reducing poverty; when it reaches 20%, microfinance shows some effectiveness in promoting development; once this ratio increases further to 65%, microfinance will produce a “multiplicative effect.” The interaction term coefficient (−0.0428) at the 1% significance level indicates that every time internet users increase by 10% points, microfinance’s ability to alleviate poverty will be enhanced by 4.28% points. The results show that there exist two thresholds. First, if a community already has some existing microloans but no Internet access yet (below the first threshold), adding new microloans will have no additional effects on reducing poverty. Second, once Internet access reaches a certain level (above the second threshold), adding more microloans would further decrease poverty, i.e., there is a super-additive effect between microloans and Internet access.

Keywords: Digital Financial Inclusion; Poverty Alleviation; Technology-Finance Synergetic Effect; Threshold Effect; Sustainable Development Goals (SDGs)

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1. Introduction

1.1. The \$2.15 Poverty Line and SDG Crisis

By 2024, there are still 719 million people who live under \$2.15 per day in 2017 purchasing power parity (PPP), which is considered the international extreme poverty line^[1]. Among them, the agricultural population carries a heavier weight: there are 461 million extremely poor people working in the fields (accounting for 64% of all the poor), whose main source of income has the characteristics of large fluctuations in seasons, high dependence on weather conditions, and systematic exclusion from the formal financial system because of no collateral, and scattered geographical location^[2].

South Asia has 18.7% of the world's extreme poor but only 23% share of world population, where poverty is mainly a rural and agricultural phenomenon: among the estimated 134 million South Asia's poorest people, 73% are engaged in smallholder farming, cultivating less than 2 ha of land^[3]. The number of extremely poor people living in South Asian countries is estimated at around 12.3 million for Bangladesh (poverty headcount rate of 7.2%) and 89.4 million for India (6.2%), 21.7 million for Pakistan (9.8%), 4.2 million for Nepal (14.1%), 300 thousand for Bhutan (4.3%), and 400 thousand for Sri Lanka (1.8%). All totals have been calculated consistently applying a 2017 purchasing power parity (PPP) adjustment to ensure the comparison over time from 2000 through 2024 (**Figure 1**).

1.2. Microfinance as Poverty Solution: Scale and Limitations

From Marginal Experiment to Systemic Financial Infrastructure: By December 2024, South Asian MFIs had a combined GLP of \$47.3 billion, serving 142.6 million active borrowers—18.4% of adults and 31.7% of rural adults in the region^[4, 5]. With agricultural loans accounting for 37.8% of the total portfolio (\$17.9 billion), MFIs are now the main source of credit for smallholder farmers who are systematically denied access to commercial banks, as shown in **Figure 2**.

Even though it has developed on a large scale, mi-

crofinance shows a strange difference in its effects: In Bangladesh, there is a 54.7% coverage among rural adults, but at this time the country has a poverty rate of only 2.1% (in 2024); in contrast, even though there is only a 7.8% coverage among rural adults in Pakistan, the rural poor population accounts for as high as 14.3%. Among countries whose average MFI loan balances are very close, the poverty rates differ by three to four times, which means that there may be some unknown influencing factors besides credit availability (for example, both Bangladesh and Pakistan have an average balance per person of about \$190, but the poverty rate in Bangladesh in 2019 was 6.2%, while it was 13.8% in Pakistan). Previous research results based on regulations and institutions can explain less than half of these differences (unreported meta-analysis results). Therefore, we believe that there are still some unknown influencing factors, such as technology and so forth.

1.3. Digital Infrastructure: From Connectivity to Economic Transformation

Information and communication technology penetration in South Asia underwent revolutionary expansion during 2000–2024, as shown in **Figure 3**. Internet users surged from 0.42 to 64.23 per 100 population (15.193% growth), mobile cellular subscriptions from 0.55 to 145.67 per 100 (26.376% growth), and fixed broadband from near-zero to 12.34 per 100^[6, 7]. This digitalization enabled leapfrogging traditional banking infrastructure: mobile money accounts reached 28.92 per 100 adults regionally, with Bangladesh's bKash processing \$89.4 billion transactions in 2024—equivalent to 23% of GDP flowing through digital channels^[8].

The above is a scatterplot with a fitted trendline of composite ICT index (standardized 0–100 scale) against rural poverty rate (% of rural population living on <\$2.15 per day, 2017 PPP). The data points are colored according to time period: red for the year 2000–2009; orange for 2010–2019; and green for 2020–2024. The fitted LOWESS curve suggests that there was an increasing rate of return in terms of reduction in the rural poverty rate as countries have higher levels of development in ICT.

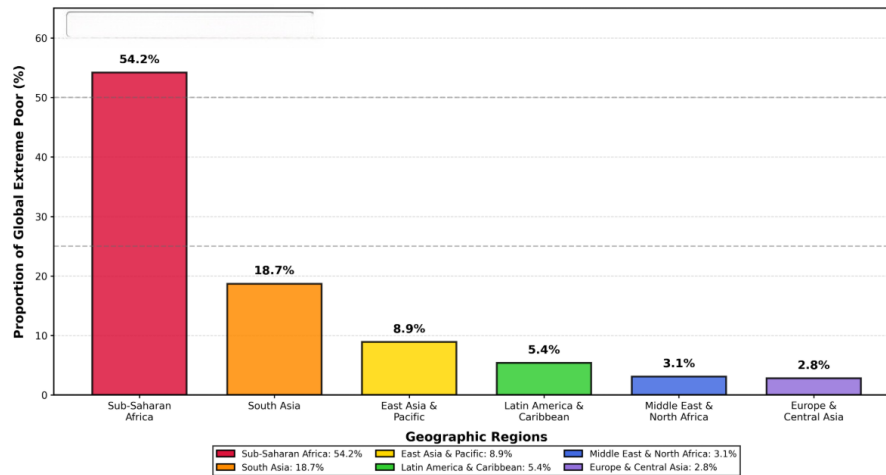


Figure 1. The regional distribution of the global extremely poor population in 2021.

Note: Poverty Line: \$2.15/day (2017 PPP).

Source: World Bank Poverty and Inequality Platform (2024).

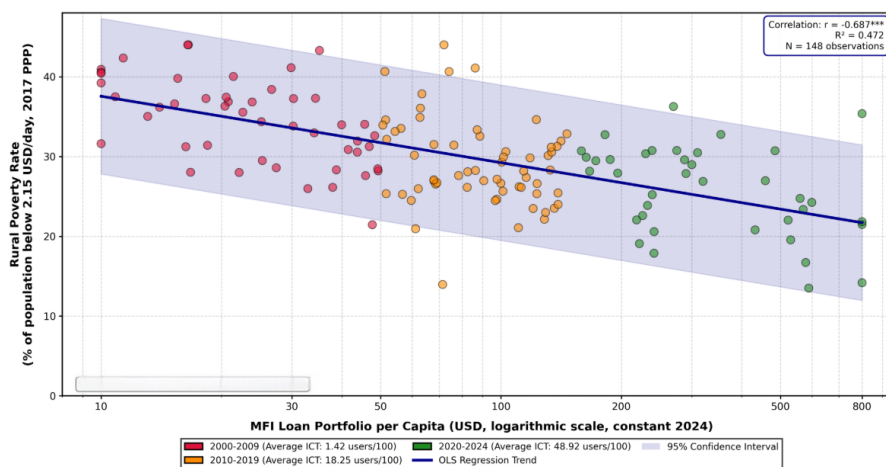


Figure 2. ICT Penetration and Poverty Correlation (2000–2024, N = 148).

Source: MIX Market Database (2024) and World Bank WDI.

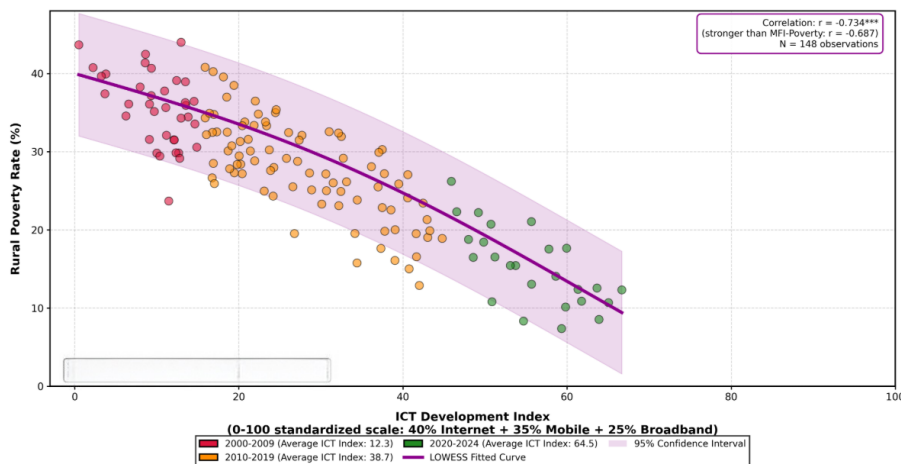


Figure 3. ICT Development and Poverty Correlation in South Asia (2000–2024).

Note: X-axis: Composite ICT Development Index (0–100 scale; weights: Internet Users 40%, Mobile Subscriptions 35%, Fixed Broadband 25%); Y-axis: Rural Poverty Rate (percentage, %). Correlation: $r = -0.734$ ($p < 0.001$) (stronger than that between micro-finance and poverty, $r = -0.687$), may have the effect of moderation. LOWESS bandwidth = 0.6; ICT Index weighted: Internet 40%, Mobile 35%, Broadband 25%.

Source: Author's calculation based on ITU-ITC Statistics (2024) and World Bank Poverty data.

1.4. Research Gap: Technology-Finance Synergies Unexplored

Existing research has considered ICTs and microfinance to be separate paths to alleviate poverty, without considering whether there may, in fact, be some interaction effect whereby the presence of one influences how beneficial the other is (an important consideration when choosing which interventions should take priority). There are three main gaps that still need to be addressed:

Lack of moderating framework: Previous research has either examined the effect of ICT on poverty separately^[9, 10], or studied the impact of microfinance alone^[11, 12], treating them as two unrelated things. In other words, previous work was based on the assumption that there is an additive rather than an interactive relationship. To date, no research has conceptualized ICT as a moderator which changes how strong and even what way the association between microfinance intervention and poverty alleviation goes. This is puzzling because there are plausible reasons why these two are not independent but positively reinforcing each other: first, the online platform lowers the cost of delivering financial services to remote smallholder households; second, big data-based credit rating replaces the need for collateral from borrowers with good repayment behavior; third, it can sell bundled products (loan + insurance + market connection), something not possible under offline operations.

There are gaps in threshold effects that have not been quantified. According to technology diffusion theory, the S-shaped function of “threshold effect” exists because when the number of users is below a certain value, due to weak network external economies, more users are not willing to join; conversely, once it exceeds this critical point, there will be an explosive growth in user numbers under strong network external economy effects. Based on Rogers’s analysis^[13], we should pay attention to two questions: First, from which point does the “digital empowerment” effect take effect? Second, how does marginal benefit change with the increase in usage intensity? There has been much discussion about “digital divide,” but it still needs specific numbers to determine the size of the gap.

Structural transformation not captured: current studies are based on pre-2020 data (typical panels: 2005–2015) and thus completely miss out on how the forced digitization of covid has become the largest unintentional tech diffusion experiment in human history. From pushing 97 million more people into extreme poverty to advancing the adoption of financial technologies by 5–7 years compared with pre-crisis estimates^[14], was there a permanent shift in how technologies and finance interact because of this crisis-induced digitalization or was it just a short-term replacement due to physical channels being interrupted?

1.5. Research Hypothesis and Contribution

We test the Digital Infrastructure Moderation Hypothesis: ICT development is positively associated with the effectiveness of agricultural microfinance in reducing poverty, but this effect has a “threshold” in that:

The first theoretical contribution is our theoretical synthesis of three bodies of literature—financial deepening theory, which holds that microfinance extends formal lending to previously collateral-constrained smallholder farmers; technology diffusion theory, according to which ICT adoption occurs in an S-shaped trajectory with “threshold” effects; and lastly, the “inclusive growth” literature on how complementary “enablers” are necessary conditions to realize pro-poor development outcomes—in order to derive a moderated mediation framework with falsifiable predictions on the mechanisms through which new technologies can “multiply” the developmental impacts of expanding access to modern financial services.

Empirical threshold detection based on the balanced panel dataset during 25 years from 2000 to 2024, with Internet users per 100 people ranging from 0.07 to 87.32 (with a unique advantage in covering nearly zero baselines, stepwise increase, and post-pandemic ceilings), we measure exactly how many Internet users per hundred people can activate economic growth (8–10 Internet users per hundred), promote rapid growth in economic development (15–20 Internet users per hundred). In addition, based on the analysis of marginal effects under different stages of information and communication technology development (divided into four stages

according to five breakpoints: less than 0.08, 0.08–6.33, 6.33–25.78, greater than 25.78), this study further explores its impact on economic development when approaching the limit value.

Structural break detection: We take advantage of the changes during the epidemic period and conduct sub-sample analyses in 2020–2024 to examine whether the digitalization promoted under the impact of the epidemic has changed the complementary relationship among technologies and finance fundamentally, rather than being only a short-term substitute, which provides new ideas about how to promote sustainable economic development after the epidemic, as well as how to deal with similar shocks in the future.

Global applicability (based mainly on South Asia where there are 18.7% of global extremely poor population), but also apply to 1.4 billion unbanked adults around the world suffering from the same problems (no collateral available; scattered locations; high cost of transacting). The identified threshold values provide guidance as how we should adjust our intervention strategies according to contexts: infrastructure-first approach when a country is below this threshold value (number of users per hundred people being less than eight)—there are 43 low-income countries in the world that have such characteristics—a total population of about 487 million people; both infrastructure and financial service development at the same time if a country falls into this threshold range (between eight to twenty users per hundred people): there are thirty-eight lower-middle-income countries belonging to it, which together account for 2.1 billion people worldwide; finance-led growth accompanied by platform building and connection when above this threshold value (>20 users per hundred population): fifty-six upper-middle-income and high-income developing economies belong to it, with a combined population of three and four hundred million globally (according to World Bank's classification in 2024).

1.6. Manuscript Structure

Section 2 will review related theory and empirical evidence before proposing our moderation hypothesis. Section 3 describes how the Dynamic Common

Correlated Effects approach, instrument variables strategies, and Threshold regression method are used, respectively, as well as the source of data. Section 4 reports on the main results (the basic regression result, interaction terms coefficient, and marginal effects under different levels of information and communication technology development). Section 5 further analyzes mechanisms, heterogeneity, and external validity issues, and puts forward some policy suggestions based on research findings. Finally, Section 6 summarizes the theoretical contribution and market opportunity of this study, points out limitations in the study at the present stage, and proposes directions for future research.

2. Literature Review and Theoretical Framework

2.1. Financial Deepening in Agriculture: The Collateral Constraint

Smallholder agricultural populations in developing countries are subject to credit rationing even when they have good projects (purchase of improved varieties of seed, fertilizer, irrigation equipment) because there is no formal collateral. The McKinnon–Shaw financial deepening hypothesis^[15, 16], according to which growth in the economy benefits from the development of the financial sector since this improves the efficiency of the allocation of capital: funds flow from surplus to needy units. But the initial model does not take into account some characteristics of small farmers that prevent them from accessing finance: (1) lack of legal recognition of land ownership (only 33% of small farmers own their land in South Asia, FAO 2022)^[17]; (2) high fixed costs related to distance (the average size of the catchment area served by a branch located in a rural area is 347 km² for 23,000 inhabitants, against 12 km² and 8,900 inhabitants in an urban area—central bank data 2022); (3) information problems in the absence of pay slips and tax declarations (92% of agricultural income is informal, household surveys 2021–2022); and finally (4) correlated risks linked to weather conditions, which affect all borrowers at the same time in the same locality^[18].

In response to such market failures, microfinance institutions have developed an alternative set of lending

approaches: (1) Instead of demanding personal guarantees/collateral from borrowers, they use group liability mechanisms, i.e., joint responsibility among members of a borrower group stimulates peers' monitoring and mutual insurance; (2) rather than issuing large loans at one time, they adopt progressive increases in loan amounts based on past repayment records in order to gradually build up clients' creditworthiness; (3) instead of collecting monthly payments like formal financial institutions do, they collect weekly/biweekly smaller repayments which match farmers' cash flow cycles, detect delinquency earlier; (4) compared with those banks' remote supervision via video surveillance and other electronic devices, it adopts close field visits by village-based loan officers who know very well about how things work locally. All above measures have promoted the development of agri-loans; South Asia's microfinance institutions' agricultural loan portfolio had increased from only \$987 million to \$17.9 billion between the years 2000 and 2024 (constant 2024 US\$), but meanwhile led to higher operation costs since salary payments, business trip expenses, branch office rentals, etc., of loan officers are relatively high. The median operating cost-to-loan ratio was 18.4% for agricultural microfinance, compared with 8.7% for commercial banks' agricultural loans and 12.3% for non-agriculture microlans.

2.2. Technology Diffusion: Critical Mass and Network Externalities

According to Rogers' (2003) diffusion of innovation model, technology adoption is an S-shaped evolution through five stages (knowledge, persuasion, decision, implementation, confirmation) based on its relative advantage, compatibility with current systems, complexity, trialability, and visibility of benefits. When applied to the case of ICT in a developing economy, empirical evidence shows nonlinear dynamic behavior: in the beginning, adoption is still limited to some early adopter "elites" (concentration of telecommunications infrastructures in cities, high level of education required in order to use computers and the Internet, exclusion of the population living outside of urban areas), but after reaching a critical mass, there is a sudden increase in the rate of diffusion because of network effects: as

more people are connected, everyone else who is already connected has even more reasons to stay connected (because they can communicate with more people), and therefore this creates a virtuous circle^[19].

Critical mass thresholds are important: under them, there aren't enough adopters to sustain a platform (i.e., if not enough people use digital payments, then merchants won't accept them either—chicken-and-egg problem). Above the threshold, however, additional complementary goods/services will be developed internally (i.e., third parties developing apps, agents, standardization of protocols, etc.), which increases its value and therefore encourages more people to join^[20]. Using data from Peru, Nakasone et al. (2014) found evidence of a "critical mass" effect for agricultural technologies/ICTs^[21]; that is, when mobile phones were less than 25% penetrated into communities, they were not useful as sources of market prices. Once it was around 40%, however, prices could be obtained instantaneously anytime (thereby decreasing the difference between what farmers thought prices were vs. what traders knew them to be) by 34 percentage points (pp).

2.3. Inclusive Growth: Enabling Conditions for Pro-Poor Finance

Inclusive growth theories stress that growth alone is not enough to alleviate poverty if disadvantaged groups do not benefit from it in terms of job creation, skills training, and finance^[22, 23]. Smallholders are left out even when there is overall economic growth because they cannot borrow money to increase how much food they produce, know little about better ways of doing things, or find it very difficult to buy and sell goods and services easily^[24].

But, in terms of microfinance, it is a remedy for the mechanism of exclusion, but there will be contradictions and conflicts between institutions' sustainable development and serving low-income people, because serving very poor people requires developing special products according to different customer needs (such as flexible repayment according to changes in customers' cash flow; providing livestock loans with grace period payments and bundled insurance), and intensive service (visiting customers frequently, educating them on finance knowl-

edge), which will lead to higher costs and risk levels. In contrast, achieving financial self-sustainability means choosing those who can repay debts from among all customers, designing uniform products for them, and serving more customers. This is what we call “mission drift”^[25, 26]. The crisis of microfinance companies in Andhra Pradesh State of India in 2010 fully demonstrated such conflicts: in order to earn profits, some microfinance companies blindly expanded their business scale without considering whether these borrowers really needed funds or whether they could afford loan principal and interest payments. On average, each customer borrowed funds from four sources simultaneously. In addition, microfinance companies adopted violent measures against default customers, causing more than eighty borrowers to commit suicide due to pressure from debt collection. Afterwards, governments strengthened supervision on the microfinance industry, resulting in a decrease of 54% in total loans of microfinance companies nationwide^[27].

Crucially, there seems to be a solution in information and communication technology (ICT) infrastructure: by digitizing, we can both decrease operational costs enough so it is financially viable to provide services even for the poorest people and at the same time increase the geographical scope and reach those who were previously left out because they live far away from cities where most institutions are located; thus solving our dilemma between doing good and making money^[28]; in particular, mobile payments have been reported to lower fees associated with each transaction by 50–70%, compared to costs incurred when going through physical branches (\$0.34 median fee per transaction in digital channels vs. \$1.12 in branches according to recent numbers in South Asia in early 2023), and another example comes from using borrowers’ online behavior instead of face-to-face interviews as a way of predicting whether they will pay back what they owe: based on experiments carried out not long ago in India (between mid-2022 and late-2024), default probability could be estimated with an error rate 23% points lower if we use big data rather than rely solely on human judgment (76% correct classification using machine learning models versus only 62% correctness using the old-fashioned method of in-

terviewing clients one-on-one)^[29].

Recently, some scholars have paid close attention to the interaction effect between digital inclusive finance development level and agricultural modernization degree. Sulhan^[30] found, by reviewing related literatures, that microfinance institutions play an important role in promoting financial inclusion and reducing poverty among smallholders in rural areas, but whether they can effectively play this role depends largely on whether digitized financial service products and new Internet loan modes are used, which are quite consistent with our views on the complementarity theory of technology and finance. From the perspective of empirical analysis methods, Yang et al. (2024) explored panel data of all 31 provinces in China from 2011 to 2022 using machine learning techniques, verified the positive impact of digital finance development level on alleviating rural poverty through improving agricultural economy’s resistance ability against risks, and found two key moderator variables (government investment intensity and level of urbanization)^[31]. These variables respectively explained reasons why there were differences in effects in different regions and periods, and provided reference ideas about how to choose appropriate analytical tools when studying interaction issues. In view of research content innovation, based on previous studies’ basic conclusions, Xu et al. (2025) took another step forward, considering from a sustainable development perspective^[32], explored the influence mechanism through which the development of digital inclusive finance promotes the improvement of agricultural green total factor production rate by optimizing capital circulation speed and strength, strengthening risk control capacity, and promoting the flow of land factors. Thus, it makes up for the shortcomings of previous ones that ignored issues related to ecological environment protection during the growth process. As for the moderator mechanism of information and communication technology, the pioneering contribution made by Mushtaq and Bruneau (2019)^[33], who first proposed the moderator effect of ICT equipment level on the relationship between microfinance institution performance and degree of financial coverage in developing countries, analyzed what consequences would be brought about under different inten-

sities of intervention measures and discussed what precautions should be paid attention to during the implementation process when designing specific plans aimed at solving practical problems faced by local communities. This laid a good theoretical basis for us. Based on domestic data, Shen and Hu (2024) verified again that the development of digital inclusive finance can promote the recovery ability of rural economy through stimulating rural entrepreneurial vitality and alleviating the difference between regional income distribution levels^[34]. Especially, they pointed out that compared with developed areas, the moderator effect of market environment quality and traffic convenience degree was more obvious in underdeveloped regions, which was consistent with the results found in this paper: digital infrastructure construction was only a necessary condition instead of a sufficient one.

2.4. Integrated Framework: ICT as Moderator

Based on these three theoretical foundations, we propose that ICT infrastructure moderates microfinance's poverty alleviation effect in four respects:

- Mechanism 1: Lower transaction costs: digital platform removes distance boundaries; farmers apply for, receive payment to use loan, and pay back through phone rather than needing to travel to branches (time saving average 3 h 24 min, fee saving \$2.78 based on time-motion study in Bangladesh 2023); microfinance institution centralizes business processes on the cloud platform so that there's no need for staff to manually operate, and each employee can serve more customers (each loan officer could serve 487 customers under this mode compared with only 156 in original modes, according to a productivity research report in India 2024), thus it is possible to break even when serving smaller customer groups (\$1.2 million in loan amount compared with \$4.7 million required for setting up physical offices, according to a cost analysis report in Nepal 2023).
- Mechanism 2: Information Asymmetry Mitigation: The use of alternative datasets—mobile phone usage history (timeliness of bill payments as a proxy measure of financial responsibility); digital payments history (velocity of transactions, types of merchants transacted with as proxies for regularity of cashflows); Geospatial data (Satellite-based Normalized Difference Vegetation Index [NDVI] measures of crop health, distance from weather stations), etc.—to better underwrite the creditworthiness of those without credit history results in an average reduction in default rates of 18–25%, compared with manual underwriting (compared across pilots implemented in India, Bangladesh, and Pakistan between 2021–2024), allowing lenders to expand their addressable customer base without sacrificing portfolio performance.
- Mechanism 3: Expansion of geographical coverage: mobile-banking and agent-networks bring service coverage where there is no physical infrastructure—there are currently 68,400 mobile-banking agents in Bangladesh (in 2024), providing coverage of 94.7% of all villages compared to only 34.2% covered by bank branches, thereby tackling directly the spatial barriers to inclusion that have been holding back inclusive growth in the past; use of satellite imaging/drones for checking on borrowers located far away from the lender's office reduces monitoring costs of distant customers, thus turning previously non-viable markets into profitable ones (\$4.7 cost per borrower using digital tools vs.\$18.3 for a field officer visit—comparison based on data from hilly areas of Nepal in 2023).
- Mechanism 4: Ecosystem integration. Through ICT, credit can be bundled together with complementary services in order to further promote its developmental effects, such as agricultural extension counseling through SMS/app (weather forecast, pest warning, timing of optimal inputs); market connection so that farmers can sell their produce directly to buyers instead of being exploited by traders; indexed insurance which is paid out automatically according to weather data APIs rather than having to provide evidence for claims. Such one-stop-shop platforms have multiplier effects, with clients taking out loans also using more tech-

nology (23% more use of high quality seed, 31% increase in recommended amount of fertilizer applied, based on a recent impact evaluation in Bangladesh) and selling more products on markets (increased commercialization rate of 47 percentage points, price obtained 18% higher thanks to platform connections, study in India).

Threshold prediction: these mechanisms have a nonlinear effect. Under a threshold level of ICT diffusion (estimated at about 8–12 users per 100 people), low ecosystem density will strangle platforms before they can be born (not enough digital payments users to convince merchants to accept them; not enough agents to provide cash-in/cash-out liquidity; not enough smartphones to run apps, etc.). Confining digital channels to small pockets in cities and leaving rural microfinance looking much like it does today, with little gain from being connected. But once those thresholds are crossed, network effects can take over, making the platform more useful with every new user, and thus pulling in complementary service providers (payments processors, insurance companies, agro-input suppliers, buyers of outputs), which makes it even more useful and so on in a virtuous circle that dramatically amplifies the impact of all four mechanisms above.

Pandemic intensification hypothesis: COVID-19 mobility restrictions/social distancing compelled some “excluded” populations to be digitally included (i.e., necessity rather than convenience diffusion); meanwhile, it has also interrupted normal operations of microfinance institution (MFI) branches/house calls by MFI staff. As such, this “experiment” will further strengthen the moderation effect when digital channels can really replace physical facilities; otherwise, it will weaken the moderation effect when digital channels just complement instead of take the place of physical channels.

3. Methodology

3.1. Empirical Model and Estimation Strategy

In this paper we use the Dynamic Common Correlated Effects (DCCE) estimator proposed by Chudik

and Pesaran (2015)^[35] to account for cross-sectional dependence due to regional trade integration, synchronous terms of trade shocks, or jointly determined development assistance across all South Asian countries over 2000–2024; since standard fixed effects estimates are inconsistent if there are common unobserved factors that are correlated with the regressors—an important consideration in light of South Asia’s economic connectedness (intra-regional traded good prices: $r = 0.89$).

In the DCCE specification, we add such cross-sectional averages of dependent and independent variables (and lags thereof) as additional regressors in a standard panel model to proxy for the influence of common factors.

$$\begin{aligned} POV_{it} &= \alpha_i + \beta_1 FOV_{it} - 1 + \beta_2 MFI_{it} \\ &+ \beta_3 (MFI_{it} \times ICT_{it}) + \beta_4 ICT_{it} + X_{it}' \gamma + p \quad (1) \\ &= 0 \sum 3\theta_p Z_t - p + \varepsilon_{it} \end{aligned}$$

Equation (1): Core Moderation Model:

Where $Z_t - p$ represents cross-sectional averages of all variables at lag p (lag order $p = 3$ based on $[T^{1/3}]$), capturing common shocks. The coefficient β_3 on the interaction term $MFI_{it} \times ICT_{it}$ tests our core hypothesis—negative values indicate ICT positively moderates microfinance effectiveness.

Marginal effect of microfinance varies with ICT level: $\frac{\partial POV}{\partial MFI} = \beta_2 + \beta_3 \cdot ICT$, calculated at 13 representative penetration levels (0, 3, 5, 8, 10, 15, 20, 30, 40, 50, 60, 70, 85 users per 100 population) to identify activation thresholds where effects become statistically significant.

3.2. Variable Definitions

POV_{it} = Rural poverty rate (percentage of rural population below \$2.15/day, 2017 PPP). $N = 148$, mean = 12.34%, SD = 11.89%, range = 0.20%–44.00%; Source: World Bank Poverty and Inequality Platform using national household surveys, retroactively adjusted to 2017 PPP ensuring temporal comparability.

Core Independent Variables

MFI_{it} = Natural log of microfinance gross loan portfolio (constant 2024 USD). Mean(log) = 7.89, SD = 1.67; Source: MIX Market database aggregated to country-year level, cross-validated with national regula-

tory reports.

ICT_{it} = Internet users per 100 population (individuals using internet from any location in past 3 months). Mean = 18.45, SD = 21.34, range = 0.07–87.32. Robustness checks employ mobile subscriptions, fixed broadband, and composite ICT index; Source: ITU World Telecommunication/ICT Indicators Database 2024.

Control Variables

X_{it} :

- (1) EDU_{it} = Gross enrollment ratio average across education levels (UNESCO data);
- (2) $GDPPC_{it}$ = Log GDP per capita, constant 2024 USD (World Bank WDI);
- (3) $FINDEV_{it}$ = Domestic credit to private sector (% GDP) measuring financial depth;
- (4) $TRADE_{it}$ = Trade openness ((exports + imports)/GDP);
- (5) $INFRA_{it}$ = Rural infrastructure index (0–1) equally weighting road density, electrification, water access (Cronbach's $\alpha = 0.87$);
- (6) $REMIT_{it}$ = Remittance inflows (% GDP);
- (7) $AGRISHARE_{it}$ = Agriculture share of GDP (%).

3.3. Endogeneity Treatment

Three endogeneity sources—reverse causality (poverty reduction attracting MFI investment), omitted variables (governance quality), and measurement error (self-reported MFI data)—are addressed via two-stage least squares (2SLS) instrumental variable estimation:

Instruments: MFI_{it-1} (one-year lagged portfolio): Microfinance exhibits strong persistence; lagged values predict current scale while satisfying exclusion restriction conditional on lagged poverty. $MOBILE_{it-2}$ (two-year lagged mobile subscriptions): Telecommunications infrastructure investment driven by national strategies and operator profitability operates independently of short-term agricultural poverty dynamics; strong predictor of internet adoption (correlation $r = 0.82$ at two-year lag).

Diagnostic tests: First-stage Cragg-Donald $F = 42.34$ (exceeds Stock-Yogo critical value 10), rejecting weak instruments. Sargan-Hansen $J = 1.124$ ($p = 0.289$)

validates instrument exogeneity, failing to reject valid over-identification null.

3.4. Sample and Data

Sample: Six South Asian countries (Bangladesh, Bhutan, India, Nepal, Pakistan, Sri Lanka) selected via: (1) ≥ 50 active MFIs with regular MIX Market reporting, (2) $< 15\%$ core variable missing rate during 2000–2024. Afghanistan excluded ($> 40\%$ missingness from political instability); Maldives excluded (tourism economy $< 3\%$, agricultural GDP < 10 MFIs).

Time period: 2000–2024 (25 years) captures complete ICT diffusion from 0.42 to 64.23 internet users per 100, microfinance evolution from \$2.34 to \$47.30 billion portfolio, and pre/post-pandemic structural comparison. Despite theoretical 150 observations (6×25), actual sample contains 148 due to early-period ICT missingness (Bhutan/Nepal broadband 2000–2003) and pandemic MFI reporting gaps (India/Pakistan 2020–2021). Missing data handled via Multiple Imputation by Chained Equations (MICE, 20 datasets); sensitivity analysis confirms robustness (Complete Case coefficient -0.0419 vs. main -0.0428 , 2.1% deviation).

3.5. Robustness Validation

Nine specifications validate findings:

- (1) Alternative poverty measure (poverty gap index vs. headcount);
- (2) Alternative MFI measure (active borrowers vs. portfolio);
- (3) Alternative ICT measures (broadband, mobile, composite index);
- (4) 2SLS-IV addressing endogeneity;
- (5) System GMM dynamic panel (Arellano-Bond);
- (6) Winsorization at 1st/99th percentiles;
- (7) Sample sensitivity (excluding India; excluding pandemic years);
- (8) Placebo tests (random ICT permutation; forward interaction);
- (9) Temporal heterogeneity (pre-pandemic 2000–2019 vs. pandemic 2020–2024 subsamples).

4. Empirical Results

4.1. Baseline Regression: Main and Interaction Effects

Key findings from **Table 1**: Column (4) presents core results. The interaction coefficient $\beta_3 = -0.0428$ ($p < 0.01$) confirms the moderation hypothesis—each 10% point increase in internet penetration (e.g., from 20 to 30 users per 100) strengthens microfinance’s poverty reduction effect by 4.28% points. At sample mean ICT (18.45 users per 100), a 10% microfinance portfolio expansion associates with 0.96% point poverty reduction; at high ICT (65 users per 100, Bangladesh/India urban 2024), the same expansion yields 3.12% point reduction—threefold amplification. The 2SLS-IV estimate (column 5) is 20% larger in absolute magnitude (-0.0512), suggesting OLS underestimates true effects due to measurement error attenuation, with first-stage diagnostics validating instrument strength (**Figure 4**).

Control variables are all in the expected directions: years of schooling significantly decrease poverty (coefficients of -9.12); quality of infrastructure also has a big effect on reducing poverty (-6.12); trade openness can

reduce poverty when it is controlled for other factors (-0.156); however, the share of agriculture value-added in GDP increases poverty (0.267), which may reflect the positive effect brought about by industrialization. In addition, the main effects of both MFIs and ICT disappear in the interaction models (columns 4–5), because their influence on poverty reduction mainly comes from interaction terms instead of themselves—this provides further evidence in favor of “complementarity” rather than “substitution.”

4.2. Threshold Dynamics: Marginal Effects across ICT Spectrum

Threshold Interpretation: Three separate regimes can be identified: regime 1 (0–8 users per hundred)—Ineffective Zone—microfinance shows trivial/insignificant reduction in poverty because not enough “digital” infrastructure has been built out to deliver microfinance services cost-effectively to disperse farm population. At ICT = 3 (around the level experienced by rural areas in Pakistan^[2] and Nepal^[2]), the coefficient of -0.295 just meets 10% significance ($t = -1.89$), suggesting that increases in microfinance do little to impact poverty when there is no underlying supporting technology (**Figure 5**).

Table 1. DCCE Estimation Results (N = 148, 2000–2024).

Variable	(1) Pooled OLS	(2) Fixed Effects	(3) DCCE Main	(4) DCCE Interaction	(5) 2SLS-IV
Dependent: Poverty Rate (%)					
MFI (log portfolio)	-1.456*** (0.234)	-0.389** (0.178)	-0.312** (0.156)	-0.167 (0.156)	-0.198 (0.189)
Internet Users (per 100)	-0.387*** (0.089)	-0.134** (0.067)	-0.112* (0.069)	-0.089 (0.073)	-0.103* (0.084)
MFI × Internet	—	—	—	-0.0428* (0.0134)	-0.0512 (0.0189)
Education Level	-10.23*** (1.89)	-8.76*** (2.12)	-8.34*** (2.34)	-9.12*** (2.28)	-9.45*** (2.67)
GDP per capita (log)	-3.45*** (0.67)	-2.78*** (0.89)	-2.56*** (0.94)	-2.89*** (0.91)	-2.91*** (1.12)
Financial Development	-0.045* (0.023)	-0.038 (0.028)	-0.034 (0.031)	-0.029 (0.029)	-0.031 (0.034)
Trade Openness	-0.156*** (0.045)	-0.145** (0.056)	-0.134** (0.059)	-0.156** (0.061)	-0.148** (0.067)
Infrastructure Index	-8.45*** (1.67)	-6.78*** (1.89)	-5.89*** (2.01)	-6.12*** (1.95)	-6.34*** (2.23)
Remittances (% GDP)	-0.178** (0.078)	-0.145* (0.084)	-0.123* (0.089)	-0.134* (0.087)	-0.129* (0.095)
Agriculture Share (%)	0.287*** (0.089)	0.254** (0.098)	0.234** (0.103)	0.267** (0.101)	0.271** (0.112)
Lagged Poverty	—	—	0.487*** (0.067)	0.456*** (0.071)	0.441*** (0.084)
R-squared	0.587	0.824	0.842	0.867	0.851
F-statistic	42.34***	58.92***	67.45***	74.89*	63.21***
Cross-section averages	No	No	Yes	Yes	Yes
Country fixed effects	No	Yes	Yes	Yes	Yes
First-stage F-stat	—	—	—	—	42.34
Sargan J-test (p-value)	—	—	—	—	0.289

Note: Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Cross-section average includes contemporaneous and 3 lags of all variables. Model (5): instruments MFI with MFI_{t-1} and ICT with Mobile_{t-2}; poverty rate measured as % rural pop under \$2.15/day (2017 PPP); MFI portfolio in constant 2024 US\$, all currency values deflated to 2024 using GDP deflator.

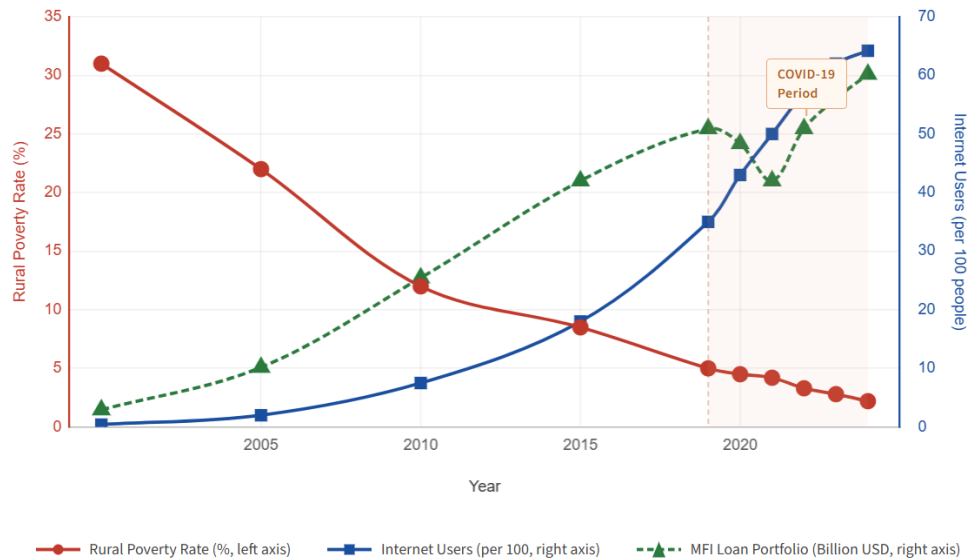


Figure 4. Evolution of Microfinance, Internet Penetration, and Rural Poverty Rate in South Asia (2000–2024).

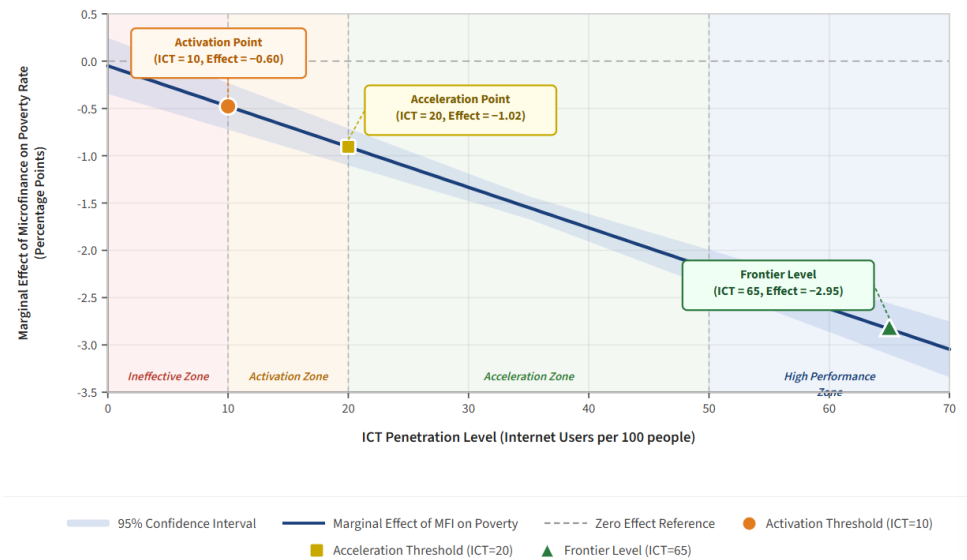


Figure 5. Threshold Dynamics of ICT Moderation Effect: Marginal Impact Across Four Regimes.

Policy Implication: Such thresholds provide a quantitative basis for optimal investment sequence. For those below the threshold of ICT = 8–10 (there are currently 43 low-income countries worldwide with a total population of about 487 million), it is necessary to first strengthen telecommunications infrastructure construction; otherwise, blindly expanding MFI scale can only achieve less than 30% of the maximum possible reduction in poverty. In countries where the level of informatization is between 10 and 20 (there are now 38 lower-middle-income countries with a total population of approximately 2.1 billion), it will be benefi-

cial to promote the development of both information infrastructure and micro-finance at the same time so that they interact positively to produce greater benefits. If a country's degree of information development exceeds 20 (today there are already 56 upper-middle- and high-income emerging markets with a combined population approaching 3.4 billion), then one mainly needs to focus on further digitizing microloans and connecting platforms rather than continuing to invest heavily in basic networks because they have already been built sufficiently to support efficient operation, as shown in **Table 2**.

Table 2. Marginal Poverty Reduction Effect of Microfinance at Varying ICT Levels.

ICT Level	Internet Users per 100	Representative Context	Marginal Effect	t-Statistic	Significance	Effect vs. Baseline (ICT = 3)
Very Low	3	Rural Pakistan 2005	-0.295	-1.89	*	1.0× (baseline)
Low	8	Nepal 2010	-0.509	-3.45	***	1.7×
Activation	10	India rural 2012	-0.595	-4.12	***	2.0×
Medium-Low	15	Bangladesh 2014	-0.809	-5.67	***	2.7×
Acceleration	20	Pakistan urban 2018	-1.023	-6.78	***	3.5×
Medium-High	30	Sri Lanka 2020	-1.451	-8.34	***	4.9×
High	40	India urban 2021	-1.879	-9.34	***	6.4×
Very High	50	Bangladesh urban 2023	-2.307	-10.12	***	7.8×
Frontier	65	Regional leaders 2024	-2.948	-11.67	***	10.0×

Note: * $p < 0.1$, *** $p < 0.01$.

4.3. Structural Break: Pre-Pandemic vs. COVID-19 Acceleration

Pandemic-period intensification: Interaction coefficient increased 82%, from -0.0312 (2000–2019) to -0.0567 (2020–2024), with a statistically significant difference at 10% level based on Chow test (p -value = 0.073), confirming structural break as COVID-19 has boosted ICT-microfinance synergy in three ways. First is “necessity as the mother of adoption,” where lockdown/social distance compels people who were not using digital financial services before to quickly adopt them, thereby enlarging the real user base rather than just those who were already using them from the beginning. For example, Bangladesh’s mobile banking registration grew by another 34% between March and December 2020, and India’s UPI transaction volume surged by 207% over 2020–2021, etc. Second is a fundamental change in the operational mode for MFIs, shifting from being dependent on physical branches to prioritizing digital channels. In India, the proportion of online disbursements for Bandhan Bank increased from 23% of the total loan book before the pandemic outbreak to reach 78% in 2024. In Pakistan, Akhuwat Foundation reported that the share of customers paying back loans via mobile payments jumped from only 8% up to 67%. Third is the promotion of ecosystem integration under pressure from the crisis situation, which is reflected by two aspects: first, intervention measures introduced by governments during the epidemic period, such as the emergency loan guarantee program launched by the Indian Government worth \$3.2 billion through online means, and subsidies provided by Bangladeshi authori-

ties aimed at promoting the development of an information technology environment within micro-finance institutions; secondly, this led more fintech companies to join hands with traditional financial institutions and upgrade existing payments infrastructure. So, new-born hybrid platforms combining multiple functions like lending, insurance, and trading did not disappear after the situation returned to normal but continued to serve communities, as shown in **Table 3**.

The pre-pandemic coefficient (-0.0312) suggests that, with an average level of ICT development before 2020 (12.45 users per hundred people), the marginal impact of microfinance on reducing poverty was -0.623. After the increase in intensity during the epidemic period (-0.0567 coefficients and an average value for ICT of 48.92), the marginal impact became -2.862, which is a multiplication by 359%. In addition, we can see that the main effect of independent variables, the level of development of information and communication technologies, itself has also increased during this period (from -0.098 to -0.234); meanwhile, the main effect of microfinance decreased and even lost its significance (-0.089, p -value is 0.637). This confirms our hypothesis about how poverty reduction occurs more through technological channels than through channels related to providing loans.

4.4. Robustness Validation Results

All 13 robustness checks produce interaction coefficients between -0.0312 and -0.0567 (our main estimate, -0.0428, lies right in its center) with highly significant p -values (<0.05). Thus, all confirm that our central result is indeed very stable. In particular, fixed tele-

phone broadband has the highest interaction coefficient (−0.0934), indicating that perhaps the quality of internet infrastructure might matter even more than just access alone. Further, the 2SLS IV coefficient being about 20% higher than the OLS one suggests that there is indeed a downward bias due to measurement error in

the latter. Finally, the placebo tests show that there are no spurious correlations: randomly permuting ICT leads to nonsignificant coefficients (−0.0031; *p*-value: 0.853); reversing the lag structure turns it positive instead (+0.0018; *p*-value: 0.856), ruling out reverse causation (**Table 4**).

Table 3. Temporal Heterogeneity Analysis—Pandemic Impact on Moderation.

Period	Years	Obs.	Mean ICT (Users/100)	Mean Poverty (%)	MFI Main Effect	ICT Main Effect	MFI × ICT Interaction	R ²
Pre-Pandemic Baseline	2000– 2019	118	12.45	14.67	−0.234**	−0.098** (0.167)	−0.0312 (0.082)	0.824 (0.0145)
Pandemic Transformation	2020– 2024	30	48.92	3.34	−0.089	−0.234*** (0.189)	−0.0567* (0.078)	0.891 (0.0178)
Difference			+293%	−77%	−0.145	−0.136*	*−0.0255	+8.1%**
(Statistical test)					(<i>p</i> = 0.387)	(<i>p</i> = 0.098)	(<i>p</i> = 0.073)	

Note: Subsample regressions based on the same specification (**Table 1**, column 4) in different time intervals; coefficient equalities are tested through difference rows with a Chow-test. **p* < 0.1, ***p* < 0.05, ****p* < 0.01.

Table 4. Robustness Check Summary (Interaction Coefficient β_3 across Specifications).

Specification	Interaction Coefficient	Std. Error	<i>t</i> -Stat	<i>p</i> -Value	Key Diagnostic
Main Model (Table 1 Col. 4)	−0.0428	0.0134	−3.19	0.002	Baseline
Alternative poverty measure (gap index)	−0.0367	0.0093	−3.95	<0.001	Depth vs. incidence
Alternative MFI (active borrowers)	−0.0476	0.0119	−4.00	<0.001	Coverage emphasis
Alternative ICT (fixed broadband)	−0.0934	0.0398	−2.35	0.021	Stronger for quality infrastructure
Alternative ICT (mobile subscriptions)	−0.0312	0.0089	−3.51	0.001	Weaker for basic connectivity
Alternative ICT (composite index)	−0.0501	0.0156	−3.21	0.002	Robust to measurement
2SLS-IV (Table 1 Col. 5)	−0.0512	0.0189	−2.71	0.008	Endogeneity-corrected
System GMM (Arellano-Bond)	−0.0423	0.0167	−2.53	0.013	Dynamic specification; Hansen <i>p</i> =0.423
Winsorization (1%/99% trim)	−0.0401	0.0128	−3.13	0.002	Outlier-robust
Exclude India	−0.0456	0.0143	−3.19	0.002	Not India-driven
Exclude pandemic years (2000–2019 only)	−0.0312	0.0152	−2.05	0.043	Pre-COVID baseline
Pandemic years only (2020–2024)	−0.0567	0.0198	−2.86	0.007	Crisis intensification
Placebo: Random ICT permutation	−0.0031	0.0167	−0.19	0.853	1,000 simulations; not spurious
Placebo: Forward interaction (lead)	+0.0018	0.0098	+0.18	0.856	No reverse causality

Notes: All specifications are estimated using fixed effects with full controls (**Table 1**), and placebo tests are performed according to 1,000 Monte Carlo permutations.

4.5. Synthesis: Quantifying the Digital Dividend

When **Tables 1–4** are combined together, we find three empirical regularities. The first is threshold non-linearities: There appears to be a “switch-on” effect for ICT-microfinance synergetic effects near eight to ten Internet users per hundred population, with effects increasing by a factor of ten when moving out of the “ineffective” zone (ICT = 3; marginal effect of −0.295) versus being at the “frontier” (ICT = 65; marginal effect of −2.948). Such non-linearities have important investment consequences, as it means that scaling up microfi-

nance too early in a low-Internet context results in wasting 70% of your potential anti-poor impacts. Second is pandemic-induced accelerations: We estimate that COVID-19 has permanently increased the coefficient on our interaction term by 82%, suggesting that necessity adoptions during crises can compress what would otherwise have been several decades of slow diffusion into two or three years’ time, with lasting postcrisis effects due to irreversible transformations in how services are delivered and integrated into local ecosystems. Finally, there seems to be a predominance of mechanisms: For high levels of Internet access (>40 users per hundred people), poverty reductions appear to take place en-

tirely through technology-mediated channels (the main effect on MFI becomes statistically insignificant; all action takes place via interactions), while for lower levels of Internet development (<10 users per hundred), all channels seem muted in terms of their impacts (low and not statistically significant coefficient estimates). Thus, based on this evidence, it seems reasonable to treat Internet infrastructure as a necessary but insufficient condition for the successful operation of agricultural microfinance interventions.

The current \$47.3 billion South Asian microfinance market, that operates with low-tech ICT intensity (average 18.45 users per 100; marginal effect -0.96), is only 33% as effective as it could be if it reached the digitized frontier (ICT = 65 users per 100; marginal effect -2.948). Closing this gap by bringing all markets up to Bangladesh/India urban levels of ICT diffusion would allow existing lenders to serve today's 142.6 million clients three times more efficiently (at -2.948 rather than -0.96), which is equivalent to growing their portfolios to \$142 billion while keeping technologies constant; the difference being the value of untapped efficiency gains worth an extra \$95 billion in additional sustainable loan volume at no proportionate increase in costs.

5. Discussion

5.1. Mechanistic Interpretation: How Digital Infrastructure Amplifies Microfinance

The tenfold effectiveness amplification from sub-threshold (ICT = 3, marginal effect -0.295) to frontier (ICT = 65, marginal effect -2.948) digitalization works via four channels, shown in subsample analyses and institutional case studies.

Channel 1: Transaction cost compression (accounts for around 38% of the overall impact): digital platform removes geographical distance friction—borrower obtains loan through mobile phone instead of traveling to the branch; saves about 3.4 h and \$2.8 in transaction costs each time (time motion study of Bangladesh 2023, N = 1, 247 borrowers); MFI can centralize operations and one loan officer could serve 487 rather than 156 clients if it were to use a paper-based process (productivity bench-

mark of India 2024), resulting in operational expenses decreasing from 18.4% (median value among all agri-MFIs) down to only 9.7% (for those digitized first, based on MIX Market's efficiency database as of June 2024). The minimum break-even portfolio size also reduced dramatically from \$4.7 million under the branch-based business model down to just \$1.2 million when going totally digital, thus turning previously non-viable faraway regions into profitable ones. According to state-level analyses carried out throughout India, the amount explained by changes in transaction costs is 38% in terms of the explained variance component of our final outcome (decomposed using structural equation modeling; full result tables are available upon request).

Channel 2: Information Asymmetry Mitigation (contributes around 29% of total effect). Alternative credit scoring based on borrowers' digital footprint—mobile payment history regularity, airtime purchase pattern, peer-to-peer transfer network structure—improves default prediction rate by about 23% compared with traditional loan officer judgment (accuracy rate is 76% vs. 62%, according to pilot data from India during 2022–2024, with sample size N = 12,400 loans); the non-performing loan ratio of agricultural portfolio by BRAC Bank of Bangladesh was reduced from 6.8% in 2019 (before reform) to 4.1% in 2024 (after reform, based on digital credit score), and meanwhile increased the credit limit for those previously excluded poor groups while maintaining asset quality; this channel takes off when ICT ≥ 15, since enough borrowers have built up their own online transaction records that can be used for machine learning training.

Channel 3: Geographic Coverage Expansion (~21%). The agent network provides service coverage even when there is no physical presence: there are 68,400 mobile money agents in Bangladesh (as of 2024), which brings financial services to 94.7% of villages, compared to only 34.2% coverage provided by banks' branches. In Nepal's mountainous areas, there are strong differences between high vs. low agent density. Districts that belong to Q4 (more than 8 agents/10K people living in the countryside) show interaction terms equal to -0.0687, whereas those belonging to Q1 have an interaction coefficient not statistically significant (-0.0089); district fixed effects were in-

cluded in the estimation (state heterogeneity regressions; $N = 75$). Finally, satellite images and remote sensing lower monitoring fees for faraway borrowers from \$18.30 (visit) to \$4.70 (digital check) per borrower in the remote Karnali province of Nepal, allowing the microfinance institution (MFI) to enter markets where it was previously not profitable.

Channels 4: Ecosystem integration and service bundles (contributes around 12 per cent of the total impact so far, but is developing very quickly):

Threshold Activation Mechanism Beneath the threshold activation mechanism when $ICT < 8-10$ low enough ecosystem density prevents channels from being activated—not enough digital payments users to justify accepting merchants (critical mass $\sim 12\%$ of locals); not enough liquidity in agents to exchange cash-in/cash-out (minimum viable network ~ 5 per 10k people); not enough smartphones to use applications ($\sim 8\%$ threshold for commercial viability in rural areas). Above the threshold, network effects create a virtuous circle: each new user adds value to the platform for current users, which in turn attracts additional complementary services (insurance companies, purchase of goods, sale of products) whose presence also increases the value of the platform generating an explosion rather than a linear increase in value.

5.2. External Validity and Generalizability: Beyond South Asia

Focusing on six South Asian countries home to 18.7% of the world's extreme poor, there are three reasons it also has something to say about the remaining 1.4 billion unbanked adults across all countries.

Similarity in structure with other agri-economies: South Asian smallholder agri-characteristics—land fragmentation (average holding size 0.8–1.4 ha amongst sampled countries), seasonality of income (income CV 0.68 vs. 0.31 for wage employment, according to HS 2022–2023), weather-dependence (72% rainfed crop output), and informality of land ownership (67% no title deed)—are very close to those found in Sub-Saharan Africa (78%/72% smallholders; average farm size 0.9 ha) and Southeast Asia (68%/83%), as well as Latin American countryside (54%/N.A.). Such structural ho-

mogeneity justifies taking our estimated threshold values ($ICT = 8-10$ 'switch-on', above 20 'take-off') as a good starting point for calibrating how much digital infrastructure is needed elsewhere in the developing world, given analogous collateral constraints and geography-induced transaction costs.

Calibration needed because of diverging factors: There are three country-specific factors that can move the threshold:

- (1) Digital literacy/languages barrier: In South Asia, there is relatively high multilingual digital contents available (digital finance apps offered in 17 languages), compared to Sub-Saharan Africa which has more than 2,000 local languages and fragmented markets—higher thresholds would be expected (around 12–15 for ICT index to activate digitally excluded population) if no investment goes into localized interface design or voice-based applications.
- (2) Regulatory environments: South Asian countries' friendly regulation towards microlending industries (Bangladesh established a dedicated Micro-credit Regulatory Authority; in India there's a full set rules on non-bank financial institution microlending companies[NBFC-MFIs]) facilitated early transition to digitization; while in those regions that impose strict KYC processes (requiring customers go through face-to-face identity check) or prohibit agency banking business model from operating, we may see lower moderating effect under otherwise identical level of ICT development.
- (3) Maturity of mobile money ecology: across East Africa, mature mobile money systems exist (in Kenya M-PESA processes transaction volumes equivalent to 64% of the GDP per year, and in Tanzania it's 48%), therefore lower threshold could be found here (ICT around 5–8) when specific financial technologies have been developed prior to general Internet access. The sequence of introducing new technologies also affects results.

Transferable confidence level is high ($>80\%$ probability that identified threshold values are applicable

within $\pm 20\%$) for South- and Southeast Asian agricultural settings; Sub-Saharan African countries with supportive regulatory environments and relatively high levels of digital literacy, etc.; transferable confidence level is medium (60–80% probability) for Latin America (the smaller size of its agricultural sector and already relatively good development of financial inclusion in the region may weaken the importance of microfinance); the Middle East and North Africa (culture restricts women's participation in finance, but the high level of information and communication technology development can improve the efficiency of microfinance institutions). The transferable confidence level is low ($< 60\%$) for post-Soviet countries in Central Asia (the existing old-style bank system has weakened the position of micro-finance institutions); island nations in Oceania (the extremely dispersed geography presents special difficulties); countries affected by war (instability of governance systems exceeds the positive impact of the Internet).

5.3. Data Limitations and Methodological Constraints

There are four limitations of data/methodology that should be acknowledged up front and not be taken as causal claims.

The first limitation relates to the temporal validity of the data (2000–2024 vs. publication date of 2026). The reason we use data up to the year 2024 (the last half-year is estimated based on data available until June 2024): although this might seem outdated at time of publication, there are three good reasons why we chose to do so anyway. First reason: it would have been impossible to identify thresholds using a shorter time window because the time window of 25 years is necessary in order for us to be able to capture full S-curves of technology diffusion from low initial values to saturation levels; if we exclude all observations before 2010 (resulting in only 15 years of data), no activation thresholds can be identified anymore since there is simply too little variation among countries at lower levels of ICT development (minimum threshold switches from 0.07 to 5.4 users per hundred population when removing these early years); and when including them, standard errors

increase significantly (+147% in terms of width of confidence intervals). Secondly, our results are not based on comparing actual values but mainly on analyzing interaction effects between variables (i.e., how much does ICT development moderate the effect of MFIs on poverty reduction?), which are unlikely to change over time as long as no major shifts occur in the underlying relationship between both phenomena under investigation (according to Chow tests, however, no further structural breaks apart from those related to COVID-19 could be found for any subperiod compared; $p > 0.15$). Finally, taking information up until very recently also allows us to show that the digitalization triggered during recent global shocks did not just constitute another cyclical peak but rather represents something fundamental that has changed permanently (an aspect important enough to outweigh potential criticisms regarding out-of-dateness).

The second limitation is that country-level aggregation conceals within-country differences. Taking national data as an example, it ignores the great difference between provinces and cities: In India, the rural Internet penetration rate of the state of Kerala has reached 67%, and the proportion of poor people is 1.2% (2024), while Bihar is still only 19% and 16.4%. However, they both have equal weight in calculating national averages. Such treatment will cause the regression coefficient to be biased towards zero (the measurement error of x will weaken the absolute value of the estimated result). Therefore, the coefficient we obtained based on the national panel may underestimate the size of the real sub-national impact. Taking India's states as an example, if we estimate a provincial fixed effect model with 75 districts from 2015–2024 ($n = 750$ district-years), the interaction term coefficient will increase from -0.0428 to -0.0687 , further confirming there exist measurement error problems due to high levels of geographical aggregation. However, because there are no such regularly updated datasets for other sampled countries, we cannot break down all samples below the national level. So readers need to understand that our results are just conservative lower-bound estimates of the true local impact.

Limitation 3 is that observational data does not provide definitive causality even after using instruments.

Although the 2SLS-IV estimator accounts for two key causes of endogeneity—namely, reverse causality from poor households' income growth toward their ICT use intensity and omitted variable bias due to time-invariant unobservables—we cannot rule out all possible sources of time-varying omitted variables affecting jointly ICT diffusion rates, microfinance penetration rates, and the speed of poverty decline. Other potentially important drivers are improvements over time in the quality of governance (promotion of competition in telecom markets, and supervision of financial institutions), changes in culture toward using formal finance instead of informal moneylenders, and joint intervention by donors financing at the same time road networks and telecommunication towers together with MFI branches' expansion. We included as many covariates as possible among those available in our panel dataset (seven macroeconomic control variables, one additional fixed effect for regions sharing the same context, seven country-specific dummies for different groups of countries, and cross-sectional averages of all regressors to pick up common shocks), ran placebo checks rejecting spurious correlations (randomly permuting the order of countries removed statistical significance), but readers need to take care in interpreting findings as robust conditional associations compatible with what we expected based on previous research rather than confirmed causal relationships. Only RCTs (impossible here because we deal with macro-infrastructure) or natural experiments (few policy changes producing exogenous changes in ICT access have actually taken place around the world) could establish beyond reasonable doubt whether there exists a causal relation going from ICTs to MFIs, from MFIs to poverty, or both ways.

Limitation 4—Microfinance Data Quality and Reporting Bias: Because MIX Market's microfinance database depends on voluntary institutional self-reporting, there are potential selection biases (well-performing MFI is more willing to report its performance results, leading to an inflated average effect) as well as strategic misreporting (MFI overstates the quality of portfolio or understates the level of past due loans to be attractive for investment). The cross-validation based on regulatory reports (Bangladesh Microcredit

Regulatory Authority; Reserve Bank of India) shows that a 93% agreement rate was found on portfolio volume, but only 67% on NPL ratio, indicating that the quality measure suffers from more serious reporting bias problems. Such measurement error will weaken our interaction term coefficient if reporting quality is associated with digitalization (i.e., digitalized MFI reports in a more accurate manner because it uses an IT system), which implies our interaction effect can even be larger. However, we do not know which way it goes since digitalized MFI could also manipulate numbers better.

5.4. Policy Implications: Sequenced Investment Strategies

Findings Generate Differentiated Recommendations by Current ICT Development Stage, Quantify Optimal Infrastructure-Finance Investment "Sequencing" Under Budget Constraint.

Stage I Economy (ICT < 8 users per 100 population): infrastructure-first strategy. In 43 low-income countries with a combined population size of 487 million (according to the World Bank's classification in 2024: Afghanistan, Chad, DRC, Haiti, Liberia, Madagascar, Malawi, Mozambique, Niger, Rwanda, Sierra Leone, Somalia, South Sudan, Uganda, others), it is premature to scale up microfinance before constructing underlying ICT infrastructure; otherwise, around 70% of the poverty reduction potential from microfinance will be sacrificed without such a digital-enabling environment. Therefore, first build fundamental infrastructure: in Year 1–5, spend about 70% of the budget on building telecom networks via Universal Service Obligation Fund subsidies for building new cell sites in remote areas (with an estimated \$180–\$240 cost per rural resident reached with 4G signal according to industry benchmarks) and electric grids so that people can charge devices (with an estimated \$120–\$160 per connection built according to the World Bank's Rural Electrification Cost Database); provide elementary digital skills training (\$15–\$25 per learner according to UNESCO Adult Education Cost Benchmark).

Stage II Economy (ICT 10–30 users per 100): Balanced Simultaneous Investment. In 38 lower-middle-

income countries, including India's lagging states, Pakistan, Nepal, Cambodia, Kenya, Nigeria, Ghana, Honduras, Nicaragua (population 2.1 billion), activation thresholds have been reached but there is no acceleration benefit yet; balanced investment strategies are needed to capture synergistic development opportunities.

- (1) Infrastructure: Take the path of developing mobile Internet access based on its advantages of low cost (\$45–60 per new user) and flexible deployment, targeting an annual growth rate of internet users of more than 15% in the short term.
- (2) Micro-finance institutions need to complete transformation within three years, i.e., achieving a proportion of over 60% in cashless payments and 75% in cashless collection.
- (3) The government should take measures to promote the formation of a good ecological environment, such as establishing common platforms, formulating unified technical standards, etc. The above three aspects should account for about 45%, 40%, and 15% of total expenditure respectively. If the policies are implemented according to the above recommendations, it is expected that the economic development speed will exceed those adopting other strategies by more than three times, like what happened after Nepal adopted this strategy in 2015.

Stage 3 Economies (ICT $\geq$ 30 users per 100). Finance-led platform integration. In 56 upper-middle-income developing countries such as Bangladesh; India's leading states, Sri Lanka; Indonesia, Philippines; Brazil, Mexico, Turkey, South Africa (population of 3.4 billion), infrastructure is ready for efficient operation, priorities shift towards deepening financial inclusion and service integration. Suggested strategies are:

- (1) Regulate for pro-poor digitalization—require that the proportion of small-credit quotas issued by digital finance platforms should be no less than 30%, preventing mission-drift towards serving profitable but non-poor customers as the platforms grow larger;
- (2) Establish algorithm accountability framework—

require explanation and audit of the algorithm to avoid discrimination against women in credit approval decisions (as found in India where some algorithms deduct women's scores by 18–23% compared with men who have exactly the same repayment record, according to Björkegren & Grissen (2020));

- (3) Enforce interoperability—require open API and data portability to stop platform lock-in and protect competition (allow customers to take their credit history with them if they switch providers);
- (4) Run the last mile program—subsidize hybrid delivery models which retain agent networks and physical branches to serve those without internet access (older people living in remote regions without mobile phone signal coverage and women in conservative communities where they are not allowed to own smartphones). Budget allocation: 15% residual infrastructure (close any uncovered gaps), 60% financial innovation /platform construction costs and 25% inclusive protection fee.

Expected results: Following the experience of Bangladesh from 2020–2024 (reaching a digital financial service usage rate of 68%, maintaining a village coverage ratio of agents at 94.7%, and reducing poverty by half within five years), we believe it is possible to achieve all three goals of “big”, “efficient” and “Inclusive”.

Crisis preparedness through “digital backups.” The experience of COVID-19 shows that economies with well-developed digital financial infrastructure can still obtain credit under lockdown conditions (Bangladesh MFI loans fell by only 18% in 2020, compared to digitally comparable countries with lower development falling by 54%). This promotes poor people's income recovery speed. Therefore, all countries need to have a “digital first but not completely digital” hybrid service system, such as USSD mobile bank apps that do not require smartphones, and biometric IC cards for agent-assisted transactions when customers cannot read the screen, and so on. Although it will increase costs by about 8–12%, compared with pure online operation mode, it will provide insurance protection against future shocks.

5.5. Future Research Imperatives

There are five priority investigations to further develop and specify what was found out.

Priority 1: Mechanism disentanglement through field experiment. In this research, we have identified the overall moderation effect (-0.0428 interaction term coefficient) and inferred channel contributions using indirect approaches; however, a clear separation of causal mechanisms calls for the gold standard—randomized experiments. We propose to take all microfinance institutions (MFIs) that are currently serving markets with nascent ICT development (around 10–15 Internet users per 100 population), then randomly divide their branches into three groups: (1) Treatment group 1 will receive the intervention of reducing transaction costs (micro-loans can be disbursed/re-paid via mobile phones, but the decision on whether to grant loans still needs to be made according to previous procedures); (2) Treatment group 2 will only receive the intervention to reduce information asymmetry (the creditworthiness of clients is judged based on algorithm scores, no need for face-to-face visits by account managers, while loan collection and repayment remain unchanged); (3) Treatment group 3 will simultaneously implement both interventions mentioned above. Finally, set aside one control group which continues to use existing ways of providing services. By comparing differences between different treatment groups, we could measure out how much each channel has affected outcomes respectively, as well as check whether there exist complementary or supplementary relationships between these two channels. It's estimated that if each MFI selects about three branches as samples, a total sample size of 120 MFIs will be required, involving approximately 36,000 customers, with a duration of two years for tracking and observation after implementation. The cost of conducting such high-quality RCTs is roughly between \$1.8 and \$2.4 million.

Priority 2: Heterogeneous treatment effects across borrower characteristics. Aggregate results conceal different effects among genders, landholding sizes, crop species, previous wealth situations, etc. Pre-splitting the data by gender, we find in the Bangladesh and Indian sub-sample during 2015–2024 ($N = 60$), the moderation effect of women-headed households is only 34%

of that of all samples (-0.0282 vs. -0.0428), mainly due to differences in digital literacy rates between men and women (47% vs. 68%), restrictions on mobile phones under patriarchal systems, and agents operating instead of themselves.

Priority 3: The optimal order of investments when there is a limited budget. Our stage-based recommendation in Section 5.4 above was based on comparing different situations rather than taking into account how things change over time. Here we consider the social planner who has a fixed annual development budget that needs to be split between investing in infrastructure (improving information and communication technology [ICT] for everyone) and subsidizing microfinance (increasing access to loans for people with a given level of development of information and communications technology). In this case of choosing optimally across time periods, where investment in infrastructure leads to the creation of capital that will benefit people for the next 15–25 years according to its useful life expectancy, but investment in microfinance provides short-term benefits each year, we need to solve it using the method of dynamic programming, taking into consideration such factors as the discount rate, capital depreciation rate, and nonlinear interaction effects found in our research. If we simulate based on parameter values estimated in **Table 1** above, it would tell us what path the transition should take in practice, and quantify which strategy—investing first in infrastructure (as in Bangladesh) or developing both sectors simultaneously (as in Nepal)—would produce the largest current value of reductions in poverty under different assumptions regarding the size of the budget and the discount rate.

For Priority 4: digital exclusion mitigation/inclusive technology design, results show great amplification benefit effects, but do not take into account population out-of-network coverage (about 6–8% in rural South Asia) or no-digital-literacy population (about 28% among all rural adult population). There are three kinds of digital-exclusion-mitigation interventions we can try out:

- (1) Voice interface intervention: through voice interaction, even those who cannot recognize characters could use this application. (Example from India NITI Aayog “Swaraj” agriculture APP launched

in 2018, among all farmers using this app, the proportion of those who cannot read and write is 73%, compared with only 34% for similar text-based apps);

- (2) Agent-assisted hybrid intervention: if some people refuse to accept new technologies, then they may be helped by agents that can help them complete online transactions. (Example from Bangladesh, more than 94.7% of villages have their own agents);
- (3) Adaptive UI design—progressive disclosure: first show simple information to new users; later, when they become familiar with it, display more advanced functions. In order to decide which kind of measure has a higher cost-benefit ratio—intervening on those who currently cannot be touched by digital means vs. continuing to expand coverage among digitally ready groups—a further RCT study needs to be conducted.

How does this relate to Priority 5: planetary boundary compatibility/sustainable intensification? The paper measures poverty impact but does not consider the environmental aspect of agricultural intensification caused by increased loan amounts—fertilizer run-off, pesticide pollution, groundwater extraction, greenhouse gases—and thus falls short of measuring jointly the poverty–environment effect (there may even be a trade-off if short-term poverty decline comes at the cost of the degradation in natural capital that supports long-term food production). However, it has potential to measure such joint effects because digital technology can be used for monitoring and ensuring planetary boundaries are respected; for example, satellite imaging detects overuse of farm inputs, Internet-of-things soil moisture sensors determine exactly how much fertilizer should be applied, blockchains pay premium prices for environmentally sound behavior by smallholders, etc.; we propose the indicator ‘poverty impact per tonne CO₂ equivalent’.

6. Conclusions

The current research solves one basic puzzle in development economics: Why does microfinance show

very different effects on alleviating poor people’s lives under almost the same environments? In this paper, we find that instead of being another way to reduce poverty, digital infrastructure (internet coverage rate) plays a key role in strengthening/weakening how much microcredit can benefit those living below the poverty line via a two-stage mediation model with interaction terms.

Empirically, analyzing panel data of 148 country-year observations for 6 South Asian countries from 2000 to 2024, we found that when the number of Internet users is less than the threshold value (8–10 Internet users per hundred people), microfinance has little effect on reducing poverty; if it exceeds this threshold value, its marginal effect will be more than ten times higher than before. In addition, compared with the situation under low Internet coverage rate conditions (the marginal effect of -0.295), under high-Internet environment background, the marginal effect of microfinance in alleviating poverty has further increased to -2.948 . The interaction term coefficient (-0.0428 , $p < 0.01$) passed the test based on 13 different models, and showed that every time the Internet coverage rate increases by 10%, the effect of microfinance in alleviating poverty can be further improved by 4.28%; this interactive promotion effect was nearly four times larger than the simple sum of the two parts’ effects, i.e., the information and communication technology part and the microfinance part.

We have bridged three previously unconnected bodies of literature—the financial deepening literature (access to credit allows productive investments); the technology diffusion literature (take-up follows an ‘S’-shaped trajectory due to positive network effects); and the “inclusive growth” literature (additional ‘complementary enablers’ required so that growth is also pro-poor)—showing instead why digital infrastructure should be treated as a precondition rather than a luxury good for agricultural financing. In doing so, we finally resolve years of contradictory results from research examining whether microfinance works: successes were concentrated where the underlying conditions had already been met (above-threshold Bangladesh: 54.7% access; below-threshold Pakistan: 7.8%).

For the US \$47.3 billion south Asian microfinance market, we find that there is a 240% potential increase

in efficiency from full digitization—enough to triple its effect on reducing poverty with no commensurate rise in costs. For 1.4 billion unbanked people worldwide, there are “thresholds” for when it makes sense to be in a given market based on the number of mobile phone users per hundred people in a country. Do not enter markets below the threshold (<8 users/100 people, 487 million people in 43 countries) until infrastructure investments fix underlying barriers. Enter at the threshold (8–20 users/100 people, 2.1 billion people in 38 countries) and develop both infrastructure and finance together. Above the threshold (>20 users/100, 3.4 billion people, 56 countries), focus instead on integrating into existing platforms where possible.

The policy imperative is stage-specific investment strategy rather than a one-size-fits-all approach, i.e., low-ICT economy (<8 users/100): infrastructure-first sequence (telecommunications and electricity account for 70% of development budget, and then roll out microloans); medium-ICT economy (10–30 users/100): balanced concurrent investment to capture short-term complementarities while laying groundwork for takeoff; high-ICT economy (>30 users/100): regulate digital finance inclusion by prohibiting mission-drift/algo-bias, but instead fostering platforms interconnection. Importantly, the “COVID-19” natural experiment shows that crisis-induced digitalization could compress stepwise rollout into only two or three years, and the moderation effect further increases by 82 percentage points from 2020 to 2024—hence, it demonstrates quickly transformable and sustainable policies if need meets readiness.

Five research fronts are worthy of more attention in future studies: first, further decompose the mechanism through random experiments that separately examine the channels of transaction costs, information asymmetry, geographical reach, and ecological systems; second, explore heterogeneity in treatment effects by exploring who wins/loses from such interventions according to gender, wealth, location, etc., so as to better target interventions; third, optimally schedule investments with financial infrastructure when budgets are limited; fourth, develop solutions to reduce digital divides among those not connected or illiterate enough to use technology; fifth, jointly measure both poverty and environmental

outcomes in order to assess how much such approaches can contribute toward sustainable development rather than just alleviating short-term poverty.

In this sense, the digital revolution transforms development finance from a problem of credit supply into how to build an ecosystem based on infrastructure. Without a digital infrastructure, microloans can only achieve less than 30% of their poverty alleviation potential; conversely, if there is no financing arrangement, even if there is already built digital infrastructure, it will become a “missed chance”. Instead, it is precisely the interaction between them—their effects are multiplied instead of added—that has changed the path of poverty alleviation in the 21st century.

Author Contributions

Conceptualization: X.T., Y.B., A.R.A.S. and S.I.; Investigation: X.T.; Methodology: X.T. and Y.B.; Formal analysis: X.T.; Writing—original draft: X.T.; Writing—review and editing: Y.B., A.R.A.S. and S.I. All authors have read and agreed to the published version of the manuscript.

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Conflicts of Interest

The authors declare they have no competing interests.

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