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Impact Assessment of Intelligent Learning Systems on Credit Discipline and Micro-Enterprise Development

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Abstract

Timely repayment and small firm performance are central to enterprise development and microfinance sustainability because predictable payments support liquidity and continued credit access. Existing fintech work lacks borrower-level causal evidence and standardized outcome measures, and this protocol confines causal claims to sampled partner microfinance branches. This pre-registered protocol defines a cluster-randomized field experiment that assigns partner microfinance branches and records the randomization script and its documented seed. Primary outcomes are borrower-level on-time repayment over a six-month follow-up and enterprise revenue change over a twelve-month window. The pre-analysis plan fixes the estimands and reports intention-to-treat contrasts using covariate adjustment, cluster-robust variance estimates, and cluster bootstrap inference with fixed seeds. These design and quality checks defined in advance aim to support credible operational decisions by microfinance institutions in partner microfinance branches.

Introduction

Timely repayment and small firm performance are central to enterprise development and to the sustainability of microfinance institutions because predictable payments support liquidity, help manage risk, and allow continued credit access for entrepreneurs. AI decision support for staff and automated reminders to borrowers could improve repayment discipline and firm revenue by sending targeted information and prompts, but practical gains depend on local payment systems and operations. This protocol defines a pre-registered cluster randomized field experiment that estimates causal effects of an intelligent learning system on borrower repayment and enterprise revenue and specifies operational outcome definitions, data quality gates, and a reproducible analysis plan to strengthen inference relative to prior studies (Oleti, 2025; Omokhoa et al., 2024).

Study motivation and questions

This pre-registered field experiment evaluates whether an intelligent learning system that provides staff decision support and sends automated reminders to borrowers affects repayment and enterprise performance in partner MFI branches (Soremekun et al., 2024). The study estimates the intention-to-treat difference between borrowers in branches using the system and borrowers in branches following usual practice for two outcomes: six-month on-time repayment and twelve-month enterprise revenue growth (Kaya, 2024).

The protocol places the trial in the fintech and SME finance literature but limits causal claims to the sampled partner MFI contexts rather than to national or cross-country development outcomes

(Siddik et al., 2024). Cross-country and macro-level evidence inform background and heterogeneity hypotheses. Any inference about broader financial development or policy effects would require external validation and replication in other contexts.

Literature Review

This protocol studies an intelligent learning system (ILS), a staff decision-support tool that sends borrower nudges, and its effects on repayment and enterprise outcomes. Systematic reviews report rapid growth in AI for consumer finance and note gaps in causal borrower impacts and measurement standards (Meng et al., 2025; Ungratwar et al., 2025; Xu et al., 2025). A cluster randomized trial with outcomes defined in advance and extraction scripts could address those gaps.

What is known and what is missing

This protocol evaluates whether an intelligent learning system (ILS) that supports loan officers and sends automated borrower reminders can causally improve on-time repayment and enterprise performance among borrowers served by a partner microfinance institution. Bank-level evidence links digital payments and fintech activity to bank outcomes and shows substitution across bank types (Alfawareh et al., 2024; Balyuk et al., 2025). Those studies do not establish borrower-level causal effects. Survey studies report that fintech platforms can expand small firm access to finance, but these analyses are cross-sectional or nonrandom and cannot isolate causal effects (Atta, 2025).

The protocol addresses these gaps and links repayment outcomes to bank risk and market signals by registering borrower outcomes in advance, fixing the index date and follow-up windows, randomizing clusters, and estimating causal effects of the ILS on repayment and enterprise outcomes (Arhinful et al., 2025). Fig. (1).

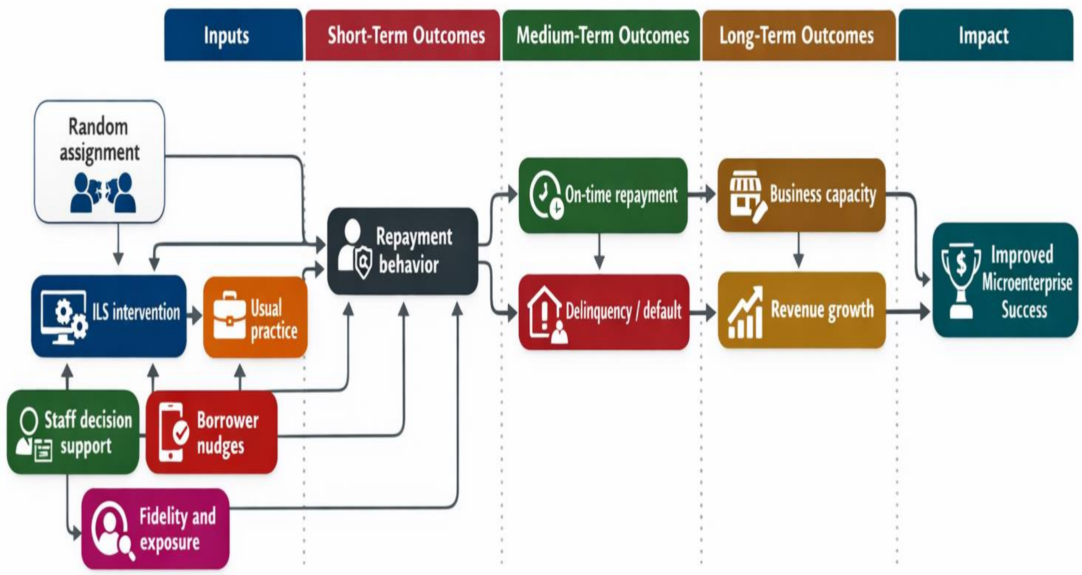

Fig. 1. Intervention-to-outcome logic model

Methodology

This pre-registered field experiment evaluates an intelligent learning system delivered through microfinance branches. It was a cluster randomized trial with 1:1 group assignment stratified by branch size and starting delinquency level. Unit of analysis: borrower. Index time: assignment date. Follow-up windows: six-month repayment and twelve-month enterprise outcomes. Observations are censored at loan closure. Randomization script and seed were recorded. Outcome: proportion of borrowers with on-time repayments over six months. Secondary outcome: twelve-month percent change in enterprise revenue linked to borrowers. Analysis estimates the intent-to-treat effect with covariate adjustment, cluster-robust standard errors and cluster bootstrap confidence intervals as in Eq. (1). Feature freeze and leakage audit preceded extraction. Sample accounting and label checks were used. Planned hierarchical testing and fixed seeds were used. See Fig. (2).

$$\widehat{\tau_{ITT}} = \frac{1}{N_1}\sum_{i:T_i=1} Y_i - \frac{1}{N_0}\sum_{i:T_i=0} Y_i \quad (1)$$

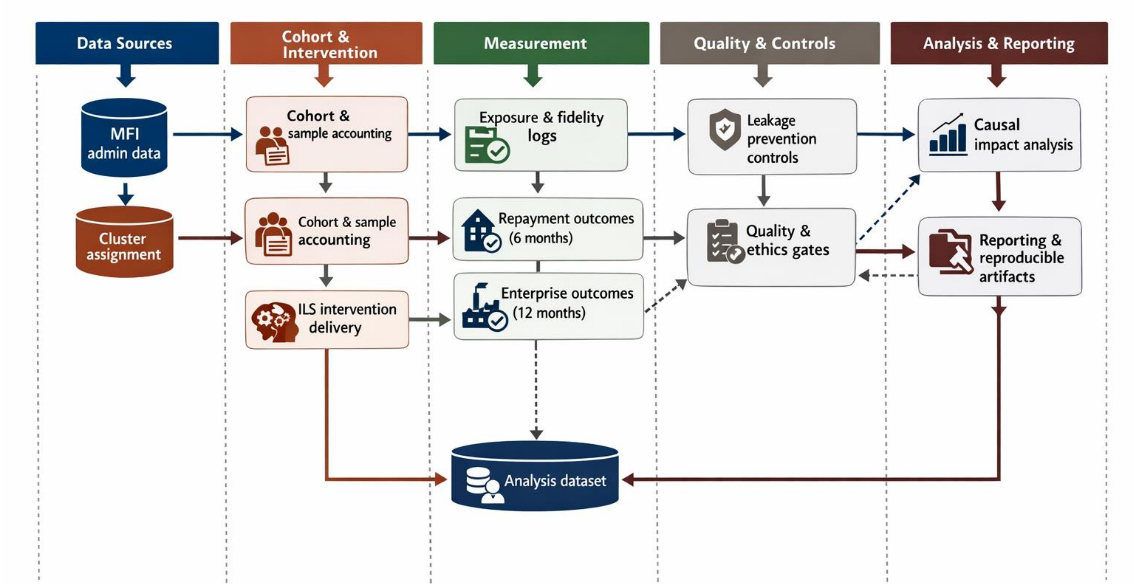

Fig. 2. Protocol workflow overview

Setting, participants, and consent

The study will be conducted with borrowers served by randomized partner MFI branches in the target country. The analysis cohort is defined at the borrower level. Eligible participants are active borrowers with at least one outstanding loan and documented consent. Exclusions are concurrent interventions and borrowers with fewer than 30 days to loan maturity at assignment. Borrower heterogeneity and planned stratification follow clustering patterns observed in prior credit studies (Ölkers et al., 2024).

A reproducible mapping script will link raw identifiers to final analysis units. An exclusion table listing excluded records with counts and reasons will be archived alongside a fixed sample accounting flowchart. Consent records, group assignment files, and exclusion logs will be retained for audit and to support replication. Starting assessment covariates used for adjustment reflect predictors used in SME distress research (Altman et al., 2024).

Intervention and control condition

The intervention uses an intelligent learning system (ILS) that helps branch staff by producing borrower risk scores that staff can understand, suggested agent actions, and automated borrower reminders. Model choices favor combined and ensemble models that balance predictive accuracy and local explainability, drawing on prior credit risk work in explainable boosted and hybrid networks (Chai et al., 2024; Monje et al., 2025; Nwafor et al., 2024).

The control arm continues standard human-driven repayment follow-up and two-way agent contact (Laudenbach & Siegel, 2024). Exposure is recorded as time-stamped delivery events and counts per borrower and cluster. Uptake and trust are measured using uptake rates, agent acceptance metrics, and short user surveys informed by adoption research (Alkadi & Abed, 2025). Process indicators defined in advance will flag shared staff or cross-cluster contacts and will feed periodic fidelity summaries to guide implementation checks.

Outcomes and measurement windows

The study measures borrower repayment timeliness and enterprise revenue change following assignment to the intelligent learning system. Index time is the assignment date. We align follow-up windows to this date so events after time zero are excluded from outcome construction to avoid look-ahead bias. The primary outcome defines on-time repayment per borrower as the proportion of scheduled installments paid on or before the scheduled payment date within a 6-month follow-up window. Censoring occurs at loan closure or exit. Tab. (1). (Gafsi, 2025)

Secondary repayment outcomes follow standard risk practice and include loan default, any scheduled payment more than 90 days past due, and mean days past due per borrower. Enterprise revenue growth is the percent change between 12-month post and 12-month pre mean monthly revenues, computed at the enterprise then linked to the borrower. Pre and post windows use 12 months before and 12 months after assignment. Measures are censored at loan closure or exit. Labels map to bank risk indicators and will be frozen before analysis (Gafsi, 2025).

Table 1. Outcome definitions and windows

Outcome	**What It Measures**	**How It Is Computed**	**Window And Censoring**
On-Time Repayment (Primary)	Payment timeliness for scheduled installments	Borrower-level proportion: count of scheduled payments with payment_date <= scheduled_payment_date divided by count of scheduled payments due	6-month follow-up after assignment date; censor at loan closure or exit
Loan Default (Secondary)	Severe delinquency during follow-up	Indicator: any scheduled payment >90 days past due within follow-up; summarized as a proportion across borrowers	6-month follow-up after assignment date; censor at loan closure or exit
Mean Days Past Due (Secondary)	Average payment delay during follow-up	Average days past due across scheduled payments within follow-up (0 if on time), aggregated per borrower	6-month follow-up after assignment date; censor at loan closure or exit
Enterprise Revenue Growth (Secondary)	Change in enterprise revenue over time	Percent change: (12-month post mean monthly revenue minus 12-month pre mean monthly revenue) divided by pre-mean; computed at enterprise then linked to borrower via enterprise_id	12 months before and 12 months after assignment date; censor at loan closure or exit

Random assignment and sample size

Borrowers were assigned to exposure to an intelligent learning system using cluster randomization at the branch or agent group level. Randomization was stratified by branch size tertiles and by starting delinquency levels. Group assignment was 1:1 and implemented by a script that yields the same group assignment on each run, with a recorded seed and an assignment timestamp. Tab. (2). Each borrower was linked to a single cluster and any overlaps were resolved using the mapping rule. The archive contains metadata.

Power calculations accounted for clustering and report a sensitivity grid across intra-cluster correlation values and attrition assumptions. Results are summarized in a power table produced by a script and saved with a commit identifier. Group assignment was 1:1 by branch size tertiles and starting delinquency levels, implemented by a script with a recorded seed. These inputs informed planned cluster counts and the target precision. Fig. (3)

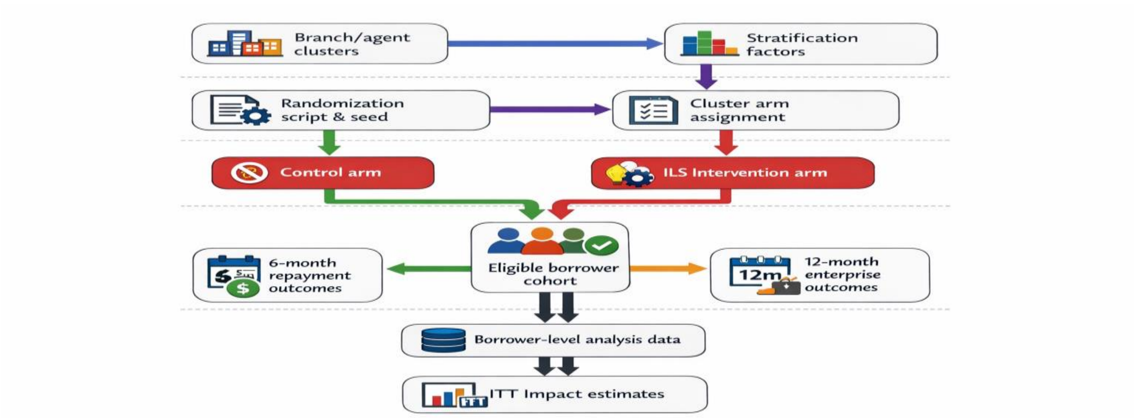

Fig. 3. Cluster randomization design schematic

Table 2. Randomization and power inputs

Input	Pre-Specified Choice	Where used
Stratification	Branch size tertiles, baseline delinquency strata	Planned 1:1 cluster randomization; implemented in deterministic script
ICC	Sensitivity grid (not a single fixed value)	Cluster-aware power and MDE calculations; power_table.csv
Attrition	Sensitivity grid (not a single fixed rate)	Cluster-aware power and MDE calculations; links to attrition diagnostics and decision rules in appendix
Randomization reproducibility	Documented seed, allocation timestamp recorded	randomization allocation file; deterministic script with recorded seed

Analysis plan

The analysis plan defines the primary estimand and estimator for the intelligent learning system on borrower outcomes. Index time is assignment date. Outcomes use a 6-month repayment window and a 12-month enterprise window, censoring at loan closure or exit. The estimand is the intention-to-treat cluster contrast ILS minus control. We report unadjusted and covariate-adjusted differences in means, adjusting for starting repayment rate, log loan size, borrower gender, enterprise sector, and branch fixed effects. These definitions were set in advance in the pre-analysis plan. Tab. (3).

Inference procedures and multiple-testing rules are set in advance. Cluster-robust variance uses cover type CR2 with a small-sample correction. A cluster bootstrap with 2000 resamples and fixed seeds will produce 95% confidence intervals and two-sided p-values at alpha=0.05. Hierarchical testing evaluates repayment first, then enterprise. We will assess sampling and label risks and report checks of agreement between predicted probabilities and observed outcomes to support decision use, following best practices in credit scoring and agreement checks (Kozodoi et al., 2025; Văduva et al., 2024). The workflow is shown in Fig. (4).

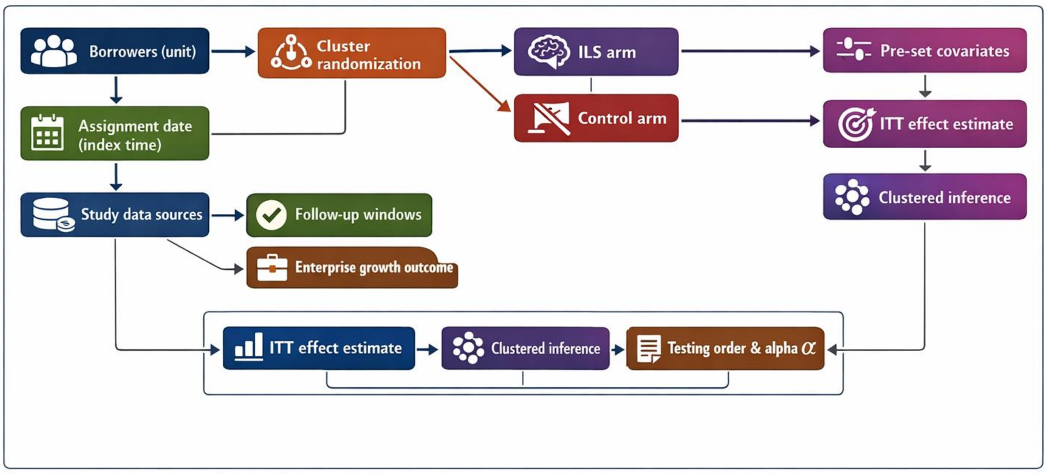

Fig. 4. Primary estimand and inference plan

Table 3. Estimand and inference plan

Plan Element	Specification	Key Details
Estimand	Average effect of assignment to ILS vs control on borrower outcomes	Index time is assignment date; outcomes aligned to index time; 6-month window for repayment outcomes, 12-month window for enterprise outcomes; censor at loan closure or exit

Main Outcomes	On-time repayment (primary) and enterprise revenue growth (secondary)	On-time repayment is borrower-level proportion of scheduled payments paid on or before due date within 6 months; enterprise revenue growth is percent change from 12-month pre to 12-month post mean monthly revenue at enterprise, linked to borrower
Estimator	ITT (intention-to-treat) cluster RCT contrast, ILS minus control	Report unadjusted difference in means and covariate-adjusted difference in means; adjustment set baseline repayment rate, log (loan size), borrower gender, enterprise sector, branch fixed effects
Inference And Testing	Cluster-robust and cluster bootstrap uncertainty with pre-specified testing order	Cluster-robust variance covers type CR2 with small-sample correction; cluster-level bootstrap with resamples=2000 for confidence intervals (fixed seeds per resample); report 95% CIs and p-values; two-sided alpha=0.05; hierarchical testing: repayment then enterprise

Handling missing data and deviations

This section defines procedures to diagnose and handle attrition, missing data, noncompliance and protocol deviations in partner MFI branches. Cohort generation applies predefined inclusion and exclusion rules, produces a fixed sample flowchart, and a mapping script linking raw identifiers to borrower records. An excluded records table lists counts and reasons. Outcomes will be censored at loan closure or exit and aligned to index time.

Primary analysis follows the intention-to-treat principle, defined as analysis of assigned groups. Predefined analyses include a per-protocol analysis and a complier average causal effect analysis, the latter estimating effects among compliers. Missing outcome data and attrition will be examined with diagnostics and handled by inverse probability weighting and bounding methods in the analysis appendix. Protocol deviations and contamination events will be logged and addressed using decision rules predefined for sensitivity re-estimation.

Data management and ethics

This section describes data governance for the field experiment in partner microfinance institution branches. Data extraction begins from ledgers and the borrower registry. The feature freeze is recorded by committing extraction scripts with a timestamp and commit hash. A leakage audit lists fields excluded because they may contain post assignment information. A fixed mapping links identifiers to borrower records. Automated repayment labels were checked against a manual audit sample and agreed 95% of the time (Vicario et al., 2024).

The protocol requires institutional review board or research ethics committee approval or a documented waiver. The manuscript will describe consent procedures, risk mitigation measures, and conflicts of interest. Data will be deidentified before analysis and access will be limited to approved requests. The data management plan will specify which fields are retained and the retention periods. Extraction scripts and the feature freeze commit hash will be archived. The study team will coordinate with regulators and experts on model governance and safeguards to address privacy and interpretability concerns (Huang, 2024).

How others can repeat this

We will share the code and environment needed to reproduce the field experiment analysis in partner MFI branches. Shared artifacts will include analysis scripts, extraction SQL, the randomization script with a documented seed and group assignment timestamp, the pre-analysis plan, and a README that describes data requests and deidentification steps. A container image and an R package lock file will record the software environment.

All scripts and documentation will be version controlled in an online Git repository with recorded commit hashes, branches, and release tags for final versions. Extraction scripts, analysis code, and the container image will include commit identifiers and the recorded group assignment timestamp and seed. A changelog will document each update and the README will explain how to reproduce results and request deidentified data.

Results

We present borrower repayment and micro-enterprise results from the planned field experiment. Results follow the order defined in advance, with the main repayment outcome first and enterprise and secondary outcomes after. Each outcome will be paired with the estimation method and measures of precision. The primary analysis will report intention-to-treat estimates comparing borrowers as assigned, adjusted for covariates, with clustered standard errors and 95 percent confidence intervals. Hierarchical testing will follow the registered ordering. We will state the primary outcome definition, including the 6 month on-time repayment rate as formalized in Eq. (2). We will include fixed sample accounting flowchart, attrition diagnostics, subgroup analyses, checks, and process indicators of fidelity.

$$\widehat{p_{ontime}} = \frac{1}{N}\sum_{i=1}^{N} I\left[y_i^{(6\,mo)} = 1\right] \qquad (2)$$

Planned outcome reporting

The planned reporting will summarize primary and secondary outcomes for the field experiment of the intelligent learning system on borrower repayment and enterprise performance. Outcomes are defined with explicit numerator and denominator rules and fixed measurement windows, and summaries will present borrower-level means, distributions, and effect sizes as absolute differences and relative changes to aid interpretation (Nkambule et al., 2024). Tables will show arm means, adjusted estimates from the estimator defined in advance, and process measures of exposure and fidelity.

We will report effect sizes with inferential summaries that account for clustering by presenting cluster robust standard errors to capture correlation within clusters, cluster-level bootstrap confidence intervals, and two-sided hypothesis tests. For multiple outcomes and metrics we will provide ranked comparisons and significance-aware summaries following recommended practice (Peykani et al., 2025).

Planned additional checks and subgroups

The protocol defines subgroup analyses, set in advance, to test how repayment and enterprise outcomes vary by borrower and loan features. Subgroups are female-owned versus male-owned enterprises, starting delinquency groups, loan-size thirds, firm sector, and region or branch groups. These analyses will examine fairness and accuracy trade-offs, following prior work (Braak et al., 2024), and will use comparison rules defined in advance.

Additional checks will estimate the primary models without sensitive attributes and without governance-related control variables to test how results change with nonfinancial signals (Wahlstrøm et al., 2024). We will apply methods to handle imbalance and reduce bias, and run planned additional checks for low intervention uptake or administrative data gaps. Primary inference will remain the main evidence. These analyses will be labelled supporting, with attrition and noncompliance sensitivity routines defined in advance.

Discussion

This protocol describes a pre-registered field experiment that will estimate the causal effect of an intelligent learning system on borrower repayment and micro-enterprise outcomes. If credible positive effects are estimated, microfinance providers could view them as evidence that expanding the system may improve portfolio performance, reduce default risk, and free working capital for firms to invest in growth in this setting. Observed changes in enterprise revenue or days past due would guide adjustments to targeting, loan sizing, and staff coaching. Effect sizes, precision, confidence intervals, and subgroup patterns will determine operational trade-offs and scale decisions. This manuscript is a protocol rather than a completed impact study and presents no impact estimates.

How findings could inform practice

The study evaluates whether an intelligent learning system that supports staff and sends borrowers tailored nudges changes borrower repayment and enterprise outcomes in partner MFI branches. If the primary outcome, time repayment defined as the borrower-level proportion of scheduled payments made on or before their due date within six months, improves under the system, practitioners in the evaluated setting may prioritize adding decision support to loan officer workflows and scaling automated borrower reminders while tracking borrower exposure and message counts as measures of delivery.

If enterprise revenue grows or loan default rate and mean days past due fall, MFIs may pilot business coaching and adjusted repayment schedules. Responsible deployment should include recorded consent, clear data use policies, routine monitoring of message counts and borrower exposure, and escalation rules set in advance and recorded in operational delivery logs.

Risks and limits of the design

The study assesses whether an intelligent learning system affects borrower repayment and micro-enterprise outcomes in partner MFI field settings. Primary threats include overgeneralizing from single-dataset machine learning benchmarks, scarce administrative data that limit reliable model training, contamination across randomized clusters, differential follow-up or missing payments, low intervention uptake, and risks from using synthetic data or generated samples to augment scarce records (Huang et al., 2025). The protocol separates protocol claims from algorithmic benchmark claims.

Protocol documentation will address these threats via quality checks, a fixed unit mapping script and sample accounting flowchart, a leakage audit with a feature freeze timestamp tied to extraction scripts, and outcome validation against a manual audit sample (N>=200, agreement >=95%). Randomization scripts with seeds, attrition diagnostics, fidelity logs recording exposure and delivery counts, and ITT (intention-to-treat) and CACE (complier average causal effect) sensitivity analyses will be reported so readers can judge inference and generalizability (Joshi, 2025).

Conflicts of Interest

This study evaluates the causal effects of an intelligent learning system on borrower repayment and micro-enterprise outcomes in partner microfinance institution branches (MFI). All authors completed conflict of interest disclosures and a COI statement is provided in the appendix. Documented ties are managed through contractual firewalls, restricted data access, author recusal from operational decisions, and independent verification of analysis procedures.

Acknowledgements

This pre-registered field experiment of an intelligent learning system for borrower repayment and micro-enterprise outcomes in partner microfinance institution branches received operational and analytical support. We thank the partner microfinance institution, branch and agent staff, participating borrowers, and the data, IT, and monitoring teams for timely access and validation, and the funders for support.

Appendices (if applicable)

Supplementary appendices support the field experiment protocol to assess the intelligent learning system's effects on borrower repayment and enterprise outcomes. They include the pre-analysis plan, reproducible randomization script and seed, outcome extraction code and a leakage audit, power and cluster calculations, a sample accounting flowchart, fidelity logs, and ethics and data management documents, and technical tables and code moved from the main text.

Random assignment and power files

For the field experiment in partner microfinance branches, we will provide files documenting random assignment. They will state the unit of randomization, the stratification variables, the assignment seed, and the assignment timestamp. The appendix will include a fixed randomization script that records the seed and algorithm and a group assignment table listing cluster identifiers, assigned arm, and counts by arm linked to the group assignment description in Methods.

A reproducible power calculation script and power table will report minimum detectable effects for the primary outcome of time repayment across a sensitivity grid of intracultural correlation and attrition assumptions. The files will record the primary metric used for sample sizing, assumed cluster sizes, the 1:1 group assignment ratio, and stratification, and will link power rows to the sample size statements in Methods.

Outcome and extraction files

This protocol lists files and templates that will define outcomes, support extraction, and enable verification under partner access limits. An outcome definitions table will list numerator, denominator, aggregation rule, and time window for each main outcome. Extraction scripts and a validation template will support comparison of automated labels to a manual audit sample of at least 200 records, with agreement at or above 95%.

A leakage audit log will record the feature freeze timestamp, the extraction script commit hash, and a table of fields excluded for post-assignment updates with rationale. Appendix files will include extraction scripts, the leakage audit, and summary checks. Sensitive individual records will be accessible to approved researchers under a documented request process that requires a deidentification plan and a data use agreement.

Conclusion

This pre-registered protocol defines a cluster-randomized trial of an intelligent learning system to estimate intention-to-treat effects on six-month on-time repayment and twelve-month enterprise revenue growth in partner MFI branches. It fixes index time, defines outcomes and follow-up windows, and locks randomization with a recorded seed to support causal inference. Credible interpretation depends on quality gates: a feature freeze audited for leakage, fixed unit mapping and sample accounting, outcome extraction validated against a manual audit with >=95% agreement, and a predefined intention-to-treat analysis that accounts for clustering.

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