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A Proposed AI-Driven EdTech Model to Improve Credit Behaviour and Enterprise Growth

[1]Dr. Bipin Sule, [2]Dr. SaiKiran Oruganti

[1]Post DoctoralResearcher. Lincoln University Malaysia

[2]Lincoln University Malaysia

Email: [1]bipin.sule@vit.edu, [2]saisharma@lincoln.edu.my

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Abstract

Learning tools powered by artificial intelligence are proposed to improve credit behavior and enterprise growth among microfinance borrowers. Existing reviews do not provide a pilot-ready blueprint that links educational content to measurable intermediate outcomes and governance for microfinance pilots. This manuscript defines a reproducible design-science blueprint and a pilot protocol that implements tailored microlearning, personalized nudges, advisory guided by predictions, and human review. The primary outcome is the on-time repayment rate measured over six months (180 days) post-index. Secondary outcomes are default and days delinquent. Deliverables include a logic model, an outcome catalogue, a pilot protocol with leakage controls, governance materials, and a synthetic data generator to support partner pilots. These artifacts enable implementers to run a governed, entity-level randomized pilot in partnership with microfinance lenders.

Introduction

This paper defines a pilot-ready design for an artificial intelligence enabled learning technology intervention to improve credit behaviour and enterprise growth among consenting micro and small enterprise borrowers. We motivate the approach using systematic reviews of artificial intelligence in consumer financial behaviour and of financial technology in microfinance (Meng et al., 2025; Offiong et al., 2024). Those reviews show theoretical promise, data opportunities, and remaining empirical gaps. We present a conceptual framework and an implementation blueprint that can be translated into a field pilot. We do not report pilot results and do not claim empirical effectiveness. Instead the manuscript provides a reproducible conceptual framework and an operational blueprint that partners can use to run a pilot. Drawing on syntheses of sustainable digital finance, we place the framework within broader thematic trends and design choices (Bansal et al., 2024). Deliverables include a one-page logic model, a pilot implementation and evaluation protocol, and governance materials covering data privacy, fairness tests, and human review rules for advisory scores and operational checklists.

Literature Review

This review places an AI-driven education technology approach for improving borrower repayment within research on AI-powered fintech, digital banking, and financial inclusion (Nefla & Jellouli, 2025; Omokhoa et al., 2024; Rifai & AlBaker, 2025; Ungratwar et al., 2025; Xu et al., 2025). Prior studies describe mechanisms such as algorithmic credit scoring, targeted nudges, prediction-informed advice, and automated recovery support, and they note risks in data privacy, algorithmic bias, and the digital divide (Nefla & Jellouli, 2025; Omokhoa et al., 2024). Systematic mappings outline frameworks for bank performance and suggest research directions (Ungratwar et al., 2025; Xu et al., 2025). Existing syntheses do not provide a pilot-ready blueprint that links educational content to measurable mediators and governance for microfinance pilots. An evidence gap map appears as Fig. (1).

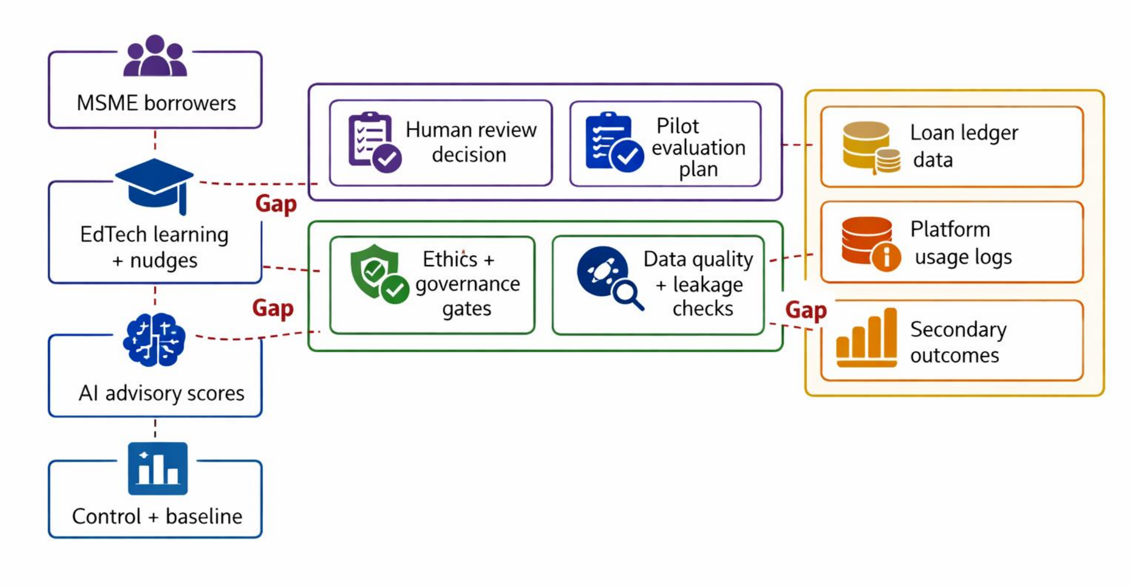

Fig. 1. Evidence gaps for AI EdTech credit

Credit behaviour and financial education

Financial education and budgeting practices influence repayment behaviour among micro and small enterprise borrowers. Better financial knowledge is linked to improved planning and budgeting, which supports on time payments (González-Prida et al., 2025). Financial literacy and use of financial technology jointly relate to firm performance and repayment patterns (Pratama et al., 2024). Digital literacy operates through changes in knowledge, attitudes, and practices to affect behaviour (Zaimović et al., 2025). These mechanisms are directly relevant to designing interventions for MSME borrowers in practice.

Design requirements follow from these mechanisms and from predictive targeting that locates low literacy users for focused instruction (Zhu, 2024). Content should prioritize product knowledge, expenditure behaviour, evaluation of digital financial tools, future assurance, and basic budgeting skills identified as high impact in factor rankings (Mohapatra et al., 2025). Modules should be short, sequenced from knowledge to attitudes to concrete practices, and paired with simple, timely nudges that translate planning into on time payments.

Digital tools and AI coaching

We review how digital delivery, personalization, and AI-assisted advice have been used in financial inclusion and credit-adjacent settings and what constraints affect feasibility and governance. Digital delivery means mobile or online channels for short learning modules and nudges. AI-assisted advice means algorithmic suggestions shown to borrowers. Studies find that platform adoption and adequate digital infrastructure condition whether fintech improves access and performance in MFIs and SME surveys across contexts (Atta, 2025; Khanchel et al., 2025; Ky et al., 2024).

Practical constraints include payment rail reliability, integration with lender ledgers, and platform uptake among borrowers. These factors affect delivery speed and message reach. Real-time payment systems and stable availability support timely nudges but require investment in rails and operations (Oleti, 2025). Governance should specify consent processes, limits on collected data, monitoring of subgroups for fairness, and mandatory human review for advisory thresholds instead of automated denial. These elements determine what is feasible and what needs careful governance.

Methodology

We converted the framework into a pilot implementation and evaluation plan for consenting micro, small and medium enterprise borrowers with partner lenders. Design fixes unit as enterprise per loan, index time at enrolment or intervention, and pilot horizon six months (180 days) post-index. Assignment is entity level, stratified by repayment quartile and sector, with a control arm and historical starting assessment. Protocol requires joins by borrower and loan id, ISO8601 timestamps, preprocessing checks, pre-index features, and a leakage checklist. Main outcome is six-month on-time repayment rate. Fig. (2) maps actors, flows, and system boundaries.

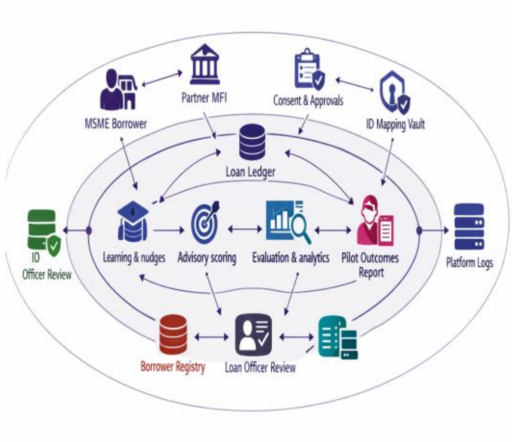

Fig. 2. Pilot system boundary and actors

Study design and setting

This study describes an artificial intelligence driven educational program for consenting micro and small enterprise borrowers served by partner microfinance institutions. The unit of analysis is the enterprise per loan episode, indexed at enrolment or at first intervention contact. The evaluation horizon is six months after index, fixed at 180 days post-enrolment, when outcomes are measured. Outcomes are aggregated monthly per loan for analysis and reporting.

Participants must be consenting adult micro and small enterprise borrowers enrolled through partner microfinance lenders. Excluded are non-business loans, minors, and any records without identifiers or documented consent. Enrolment requires borrower id, loan id, an enrolment timestamp, a consent flag, and a digital contact channel. Linkage uses borrower id plus loan id, and timestamps must follow ISO8601, the international date time standard, for precise event alignment.

EdTech and AI components

This section specifies intervention modules, required inputs, and operational roles for an AI-driven EdTech system for consenting micro, small, and medium enterprise borrowers at enrolment. The intervention combines tailored microlearning, personalized nudges, prediction-informed advisory, and a human-review dashboard integrated with the lender loan ledger. Required inputs are loan ledger events, the borrower registry with consent flags, pre-index covariates from prior repayment history and sector, and platform logs of content and timestamps. Two-way outreach by trained field agents uses personal contact to help improve delinquency resolution and reduce recurrence (Laudenbach & Siegel, 2024).

Each component has a recorded fidelity metric and a named actor responsible for delivery and monitoring in platform logs. Borrowers receive content and reply to prompts while field staff triage cases on the dashboard for human review and escalation. Automated advisory scores require human review and do not trigger credit denial. Advisory content is guided by models that provide tree-based explanations (Li et al., 2025; Monje et al., 2025) and bias controls are applied (Chai et al., 2024).

Outcomes and measurements

This section defines measurable outcomes for an AI-driven financial education intervention delivered to consenting MSME borrowers. Outcomes are anchored to the index time (enrolment or first intervention) and to a six-month pilot horizon. The primary outcome is the on-time repayment rate over the six-month horizon, defined as the fraction of scheduled payments made on or before their due dates and measured from the loan ledger. Default-related reporting and classification metrics follow established practice for monitoring (Bhandary & Ghosh, 2025; Gafsi, 2025).

Secondary outcomes include default rate at six months, mean days delinquent capped at 180 days, enterprise revenue change from pre-index starting assessment, and a validated financial literacy score. These are measurable from loan ledger, borrower registry, platform logs, and endline surveys. Over 20% missing data triggers review and imputation documentation. Tab. (1). It lists operating points and maps outcomes to the logic model, where knowledge gains and nudges are mediators for timelier repayment (Gafsi, 2025).

Table 1. Operating points and decision thresholds

Operating Point	Trigger Or Threshold	Resulting Action
Data Missingness	More than 20% missing values in any field	Flag in missingness report, review data capture, document imputation rules

Consent And IDs	Missing consent flag or missing borrower_id or loan_id	Exclude record from analysis and pilot tracking; require consent and approval records
Advisory Score	Advisory score reaches a defined threshold (cutpoints set by partner MFI)	Show advisory recommendation; mandatory human review and escalation; no automated credit denial
Post-Index Leakage	Any pre-index feature uses events after index_time	Drop or mask the feature; rerun timestamp alignment and leakage audit checks

Pilot evaluation protocol

This protocol describes how we will evaluate a field pilot of the AI-driven education and advisory system for consenting micro, small, and medium enterprise (MSME) borrowers, and it defines the comparator family and the split strategy. The study compares an intervention arm to a business-as-usual control and to a historical pre-intervention starting assessment, with entity-level assignment at enrolment stratified by prior repayment quartile and sector (Qiu & Wang, 2025; Zhang et al., 2025). Tab. (2). The primary outcome is the difference in on-time repayment rate within 6 months post-index, as defined in Eq. (1).

Analysis will estimate the arm difference at the loan episode level and report bootstrap confidence intervals for the 6-month main outcome, adjusting for stratification variables and pre-index covariates. Predictive starting assessments for advisory scores will follow ML benchmarking, including LLM prompting, tree-based models, hybrids to avoid under-comparison (Balyuk et al., 2025; Huang et al., 2025). Leakage and contamination controls will enforce timestamp alignment, drop or mask post-index features, maintain entity and time isolation, and run a leakage audit and sensitivity checks with alternate index windows.

$$OTR = \frac{N_{on_{t}ime}}{N_{scheduled}} \tag{1}$$

Table 2. Protocol splits baselines and metrics

Split Or Baseline	**What It Includes**	**Key Isolation Rule**	**Main Metrics**
Intervention Arm	Consenting adult MSME borrowers receiving microlearning, personalized nudges, advisory scoring, and human-review dashboard	Index at enrollment/first-intervention; outcomes measured post-index only	On-time repayment rate within 6 months; default rate; mean days delinquent; revenue proxy change; financial literacy score
Business-as-Usual Control	Consenting adult MSME borrowers with no EdTech intervention; same enrollment process	Entity-level assignment at enrollment (where feasible); keep feature windows pre-index	On-time repayment rate within 6 months; default rate; mean days delinquent; revenue proxy change; financial literacy score
Historical Pre-Intervention Baseline	Ledger-derived pre-index holdout window aligned to each loan episode index time	Time alignment to index time; no post-index events included in baseline features	Pre-index repayment behavior used for comparison with post-index outcomes
Leakage And Contamination Controls	Feature provenance checks, timestamp alignment checks, separate exports of ledger snapshots for baseline vs pilot arms	Drop or mask any post-index-derived feature; enforce entity/time isolation	Leakage audit checks; sensitivity checks with alternate index/horizon windows; feature ablation and missing-data sensitivity

Governance fairness and data protection

Governance framework specifies protections and controls for deploying the AI-driven education and advisory system with partner microfinance institutions, motivated by evidence that rapid digital lending growth can raise credit risk and regulatory concerns (Anestiawati et al., 2025). Consent requirements will be explicit at enrolment. Personal identifiers will be pseudonymized and the mapping stored separately with role-based access and audit logs. Data minimization and a documented retention schedule will limit stored fields and how long data are kept and why.

Operational rules require that prediction-informed advisories go to a human review step before any credit decision, with defined escalation paths and no automated credit denial. Subgroup audits will test outcomes by gender, enterprise sector, prior repayment quartile and loan size category, using metrics defined in advance and planned mitigation options to reduce disparate impacts. Ongoing monitoring, regular audit reports and stakeholder review will align governance with sustainable finance goals and SME policy considerations (Tanchangya et al., 2025) and include public transparency summaries quarterly.

Results

We produced design and evaluation artifacts to support a pilot of an AI-driven intervention for consenting MSME borrowers at partner MFIs. Deliverables are a system blueprint with specifications and metrics, a logic model and mediator map, an outcome catalogue for the six month index horizon, a pilot protocol with entity time isolation and leakage controls, and governance materials on consent, deidentification, access and human review. Assets to help others repeat the work include a synthetic data generator, a labelled sample and environment specs python==3.11.4. Equation (2) defines default as a binary loan outcome.

$$DefaultRate = \frac{1}{N}\sum_{i=1}^{N} y_i \tag{2}$$

Proposed system workflow

The proposed workflow maps the user journey for the EdTech intervention during partner microfinance loan episodes. It covers initial content delivery, nudge messages, advisory that uses predictions, and monitoring. Content delivery and basic nudges are automated. Microlearning modules are scheduled and push reminders are sent according to pre-set rules. That advisory flags cases for human review. Human reviewers make the final advisory decisions and handle escalation when advisory scores cross predefined thresholds. Fig. (3).

Each step produces structured records for evaluation and governance. Records include content served with timestamps, nudge delivery receipts, advisory scores with justification fields, and human reviewer actions with decision timestamps. Loan ledger events and on-time payment flags are linked to these records by borrower and loan identifiers. A separate pseudonymization map, role-based access logs, and retention timestamps are kept. Audit trails support leakage checks and subgroup monitoring.

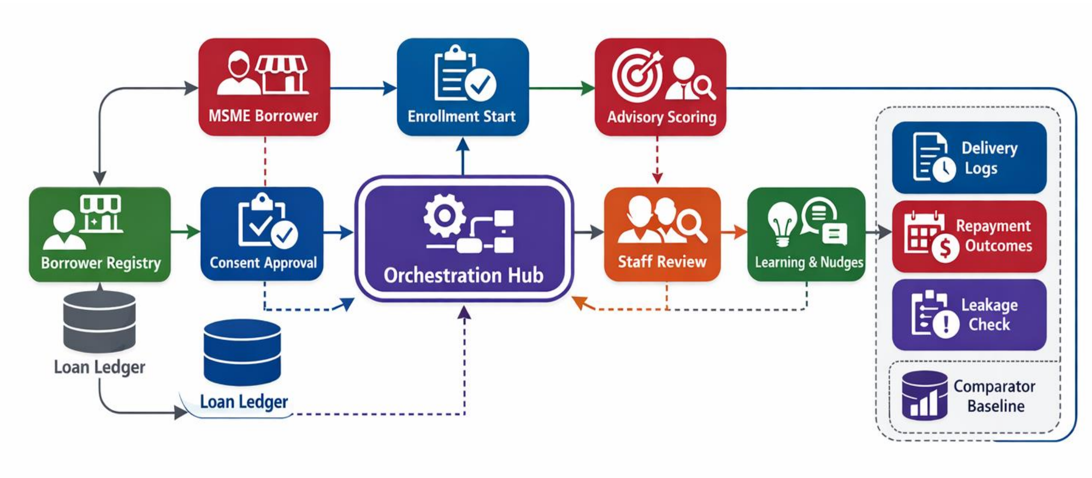

Fig. 3. To-be process for intervention delivery

Logic model and measurable indicators

The study defines a theory of change linking an intervention using AI to deliver education to micro, small, and medium enterprise borrowers to short-term learning and behaviour factors and to on-time repayment measured at six months. The model lists tailored microlearning, personalized nudges, advisories informed by predictions, and a dashboard for human review, see Fig. (4). These components operate through intermediate factors including financial knowledge, repayment intention, and payment planning within the six-month pilot.

For the pilot, each component is linked to measurable indicators and specified data sources. Tailored microlearning is measured by a financial literacy score from a brief validated instrument and by content engagement logs. Personalized nudges are paired with delivery timing, the on-time repayment rate within six months, and ledger event counts. Prediction-informed advisories map to days delinquent. The human-review dashboard records fidelity and escalation counts.

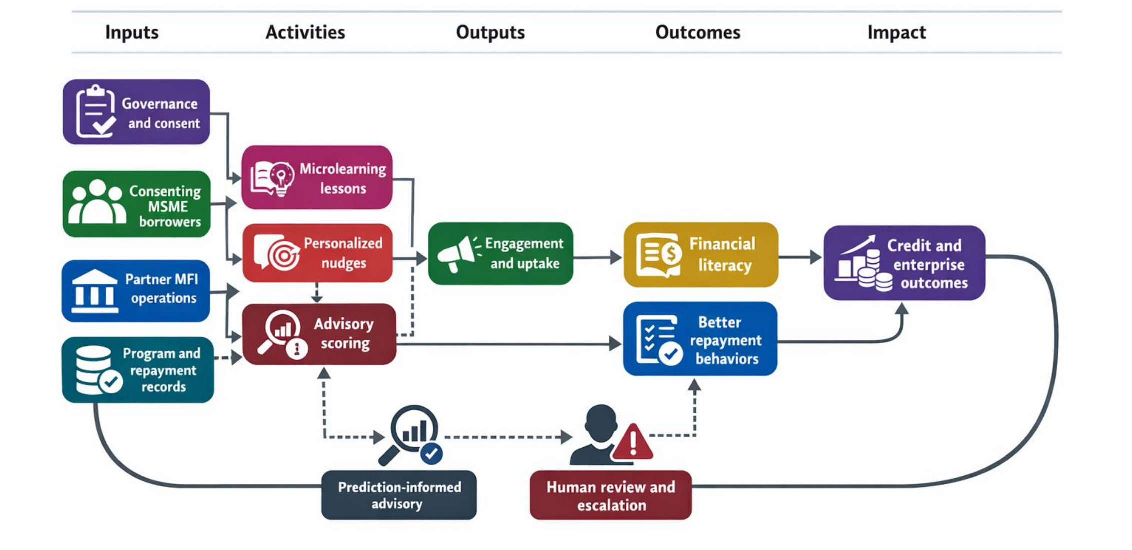

Fig. 4. Logic model from inputs to outcomes

Pilot-ready artifacts summary

Partner teams receive a package of pilot materials. It includes a one-page logic model, an outcome catalogue with operational definitions and the six-month evaluation window, the pilot protocol with split and leakage controls, a component delivery and fidelity checklist, a synthetic data generator and a labelled sample dataset, and governance materials covering consent records, a pseudonymization mapping that replaces identifiers with separate codes, role-based access controls, and logging.

The package supports implementation, evaluation, and oversight. For implementation, it gives delivery steps and fidelity metrics for trainers and operators. For evaluation, it specifies main and secondary outcomes, rules for building features before indexing, comparisons to starting assessment, and subgroup tests. For oversight, it provides consent logs, a leakage-audit checklist, documented human-review and escalation rules for advisory thresholds, and deployment monitoring tools. Full protocol details and dataset specifications are provided in the appendices.

Discussion

This study defines a blueprint for an AI driven financial education and advisory system for consenting MSME borrowers served by microfinance partners. Implementation requires combining loan ledgers, borrower registries, and intervention platform logs so the system can give tailored microlearning and nudges while preserving consent and data minimization. A valid pilot must fix the index time at enrolment, measure the primary outcome over 6 months 180 days, use a business as usual comparator, enforce entity level assignment and leakage checks, record delivery fidelity. Human review for credit adjacencies and ethics approvals must precede deployment.

Practical implications and implementation considerations

For microfinance institutions and implementers, the model defines operational tasks to integrate microlearning, personalized nudges (brief reminders), a prediction-based advisory, and a human review dashboard linked to the lender loan ledger. The advisory score uses earlier repayment history and engagement to flag borrowers who may need extra support. Staff must inspect flagged cases before any credit action and record the reasons.

Key dependencies that will affect uptake and fidelity include accurate borrower identifiers and timestamps in ISO8601 format (standard date and time), stable mobile connectivity, high consent rates, localized content, and staff capacity for timely reviews. Pilot teams should assign clear roles: platform administrator, data engineer to maintain ledger integration, loan officers for human review, and a monitoring and evaluation specialist to track delivery and engagement metrics. Teams should budget for training, monitor missing data and duplicates, and define escalation paths.

Limits risks and next steps

This manuscript presents a pilot-ready blueprint for an AI-driven educational intervention to improve on-time repayment among consenting micro, small, and medium enterprise borrowers (MSME) served by partner microfinance institutions. Key threats, limits, and mitigations are summarized in Tab. (3). Measurement limits include dependence on complete ledgers and matching timestamps. Selection risks occur if consent or identifier availability limits who is eligible. Concurrent programs can confound the behavioral pathway unless groups are separated and steps are taken to prevent information or intervention leakage. Governance safeguards are required.

Before scaling or making causal or effectiveness claims, a context-specific pilot evaluation should show improved repayment and consistent engagement and delivery fidelity across partner sites. Planned evidence should include subgroup performance checks defined in advance, formal fidelity metrics from platform logs, human review for advisory score thresholds, and documented ethics approvals, data access agreements, and consent procedures. Synthetic simulations can guide design but do not replace real-world pilot validation (Zaman et al., 2025). Scale decisions must follow replicated pilots.

Table 3. Threats limitations and mitigations

Issue	Why It Matters	Planned Mitigation
Data Access And Consent	Pilot may be blocked or key fields restricted if data access, identifiers, or consent are incomplete	IRB or ethics approval, consent procedures, data minimization and retention rules, de-identification, role-based access controls with logging
Algorithmic Bias And Subgroup Harms	Advisory scores may perform unevenly across groups, creating unfair recommendations or harms	Planned subgroup fairness tests across gender, sector, prior repayment quartile, and loan size category; mandatory human review and escalation for score thresholds
Low Uptake Or Poor Fidelity	If learning content and nudges are not used as intended, the behavior-change pathway may not operate	Track exposure and engagement using intervention platform logs (content served, timestamps, nudges delivered); use stakeholder consultations to improve fit
Limited Generalization	Findings and implementation fit may not transfer across countries or lender models beyond partner contexts	Limit claims to defined partner MFI contexts; use a business-as-usual comparator and a historical pre-intervention baseline to support context-specific evaluation planning

Appendices

The appendices collect protocol, specifications, and governance artifacts for review and replication. They include an outcome catalogue with operational definitions and the six-month index horizon, a one-page logic model with mediator mapping, a full pilot protocol on assignment and leakage controls, a fidelity specification and sample scripts, a dataset schema, a synthetic data generator with a sample row, a leakage audit checklist, conflict of interest, ethics, and data availability statements, and materials to enable repeatability: code, dependencies, and the RNG seed.

Outcome catalogue and measurement windows

Consenting MSME borrowers were studied with outcomes anchored to index time at enrolment or first intervention and a 180-day pilot horizon. Outcome catalogue links each outcome to an operational definition, data source and six-month post-index window. The primary outcome is six-month on-time repayment rate, the fraction of scheduled payments made on or before the due date in loan ledger. Secondary outcomes are lender-defined default and mean days delinquent within six months, capped at 180 days, both from loan ledger, change in enterprise revenue proxy at six months versus the pre-index assessment from ledger or validated self-report, and financial literacy score at pre-index assessment and six months using a brief validated instrument. Repayment, revenue change and literacy are higher-is-better, while default and delinquency are lower-is-better. Each outcome maps to the logic model as an indicator of the intervention pathway.

Dataset schema privacy and synthetic example

Before any pilot, partners must provide a documented dataset schema that lists required fields, the source and steward for each field, and sensitivity ratings tied to legal or consent constraints. The schema must also map each field to trial outcomes, specify de-identification and retention rules, and describe role-based access controls and audit logging. Core records required are the lender payment ledger, a borrower registry with consent indicators, platform interaction logs, and signed consent and approval records.

A synthetic example accompanies the data contract and is for integration testing only. The example includes a synthetic ledger of scheduled payments, a synthetic borrower record with a consent indicator and timestamps, and a content delivery log of nudges served. The package includes a README that documents field formats, provenance tags, and the rule used to generate labels. These synthetic artifacts are not evidence of effectiveness and are labelled for preparatory use.

Pilot protocol leakage checklist and governance

This pilot protocol specifies procedures for testing an AI-driven intervention. The intervention aims to improve on-time loan repayment among consenting MSME borrowers enrolled through partner microfinance institutions. Assignment occurs at enrolment. Group assignment is at the entity level, stratified by prior repayment quartile and sector to balance the intervention and business-as-usual control arms. Features use ledger records only. All derived predictors must use events before the index time to prevent leakage.

The evaluation protocol records the planned design and the primary outcome, the on-time repayment rate within 6 months post-index. It lists predefined secondary outcomes and a leakage audit checklist to complete before analysis. Delivery fidelity checks include verifying consent and enrolment records, matching borrower and loan identifiers, and standardizing timestamps to ISO8601. They also include complete platform logs of content served and nudge timestamps and human review dashboard activity logs. Reporting must include arm sizes, the primary outcome estimate and fidelity summaries.

Acknowledgements

We present an AI-driven education technology blueprint to improve credit behaviour among consenting micro, small and medium enterprise borrowers served by partner microfinance institutions. We thank partners and advisors for input. Authors declare no financial conflicts. Planned pilot work will seek ethics review and obtain informed consent. Appendix includes a synthetic data generator, a sample synthetic dataset and dataset schema. Partner ledger data will be shared only with permission and after deidentification.

Conclusion

This paper presents a design ready for piloting of an AI-driven EdTech intervention to improve on-time repayment and enterprise outcomes among consenting MSME borrowers. It provides a logic model, an outcome catalogue anchored to a six month horizon, a pilot protocol with entity-level randomization and leakage controls, and governance materials covering consent, pseudonymization, subgroup audits, and human review for advisory thresholds. The manuscript does not claim empirical effectiveness or causal impact without piloting. Immediate next steps are to obtain ethics and data access approvals, integrate partner ledgers, implement the randomized entity pilot stratified by prior repayment and sector, monitor fidelity and subgroup fairness, run leakage audits, and report analyses defined in advance before any scaling.

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