

Federated Machine Learning for Privacy-Preserving Credit Risk Assessment Across Distributed Financial Institutions

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Abstract

Credit risk models trained at individual financial institutions can suffer from limited observations, heterogeneous borrower populations, and restrictions on sharing sensitive financial records. This paper proposes a cross-silo federated machine learning architecture for probability-of-default estimation across distributed lenders. The design combines locally standardized borrower features, secure aggregation, differential privacy accounting, institution-aware calibration, and fairness-aware evaluation. We formulate a weighted federated objective and a reproducible experimental protocol covering temporal validation, non-identically distributed clients, membership-inference exposure, predictive utility, calibration, and operational cost. Because no institution-level data or executed experiment was supplied, all numerical tables and charts in the results section are explicitly synthetic scenario illustrations, not measured findings. The framework provides an auditable blueprint for empirical implementation while identifying the tradeoffs among discrimination, privacy, calibration, fairness, and communication efficiency.

Keywords: federated learning; credit risk; privacy-preserving analytics; secure aggregation; differential privacy; probability of default; financial institutions; fairness.

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1. Introduction

Credit underwriting converts imperfect evidence about borrower income, liabilities, payment history, collateral, and macroeconomic conditions into decisions with direct economic and social consequences. A probability-of-default model is useful only when its predicted risks are accurate, calibrated, stable over time, and sufficiently explainable to support accountable decisions. In practice, the evidence needed to build such models is fragmented across banks, credit unions, digital lenders, and regional financial institutions. Each lender observes a particular clientele and product mix; some serve salaried urban customers while others specialize in small enterprises or rural borrowers. As a result, an isolated model may generalize poorly outside its local population.

Centralizing data might increase sample size and diversity, but it also raises significant governance barriers. Financial records contain personal identifiers, income information, repayment histories, and potentially sensitive behavioral traces. Sharing raw customer-level data creates legal, contractual, security, and reputational risks. Even after direct identifiers are removed, combinations of attributes can enable reidentification. Institutions also face data-

residency requirements, competitive constraints, inconsistent feature definitions, and divergent retention policies. These practical limitations motivate approaches that exchange carefully controlled model information rather than complete customer records.

Federated learning provides a potential response. Under cross-silo federation, each institution maintains local training data and computes model updates on its own infrastructure. A coordinating server combines eligible updates to construct a shared model. This architecture does not by itself guarantee confidentiality: gradients can leak information, malicious participants may manipulate updates, and metadata can reveal participation. Therefore, federated credit modeling must integrate secure aggregation, authenticated communication, access controls, privacy accounting, and independent security evaluation rather than equating decentralization with privacy.

Credit risk assessment also differs from generic image classification benchmarks. Defaults are relatively infrequent, label observation is delayed, and missingness can be informative. A model that maximizes area under the receiver operating characteristic curve may still produce poorly calibrated default probabilities or unacceptable errors at operational decision thresholds. Furthermore, credit models operate in changing economic environments. A rise in unemployment or interest rates can shift both applicant characteristics and repayment behavior. Time-aware validation and drift monitoring are therefore essential.

Institutional heterogeneity creates a central methodological challenge. Data are not identically distributed: feature availability, default prevalence, product terms, geography, and underwriting rules differ across lenders. Simple averaging can favor large institutions and harm smaller participants. At the same time, equal weighting can underuse statistically informative observations. An appropriate design must balance sample-weighted learning, local calibration, client-specific adaptation, and performance reporting at both aggregate and institution levels.

Privacy mechanisms introduce additional tensions. Differential privacy limits the influence of an individual record on model outputs but can reduce predictive accuracy, particularly when minority borrower segments are sparsely represented. Secure aggregation conceals individual client updates from the coordinator under specified assumptions but does not prevent all attacks. Governance controls remain necessary to define who participates, which features are permissible, how model changes are approved, and what happens when a participant withdraws.

Fairness is another fundamental consideration. Historical lending outcomes reflect earlier decisions, selection effects, and economic inequalities. A federated model may inherit or amplify these patterns. Because institutions differ in customer composition, fairness analysis cannot be restricted to a pooled metric. Group-specific false-negative and false-positive rates, calibration, approval outcomes, and uncertainty should be examined where legally and ethically appropriate. Sensitive attributes should be protected and used only within approved audit procedures.

The proposed research addresses these issues by specifying an end-to-end architecture rather than presenting federation as a single training algorithm. It defines a common data contract, local preprocessing rules, client selection, robust optimization, encrypted aggregation, differential privacy options, calibration, and operational evaluation. The framework also distinguishes

development, validation, and deployment controls, making explicit the responsibilities of participating lenders and the coordinator.

The principal research questions concern whether collaboration can improve risk discrimination compared with local-only baselines, how much performance is lost under stronger privacy constraints, whether calibration and fairness remain acceptable across heterogeneous institutions, and how communication requirements scale with client participation. A defensible evaluation must report confidence intervals across repeated runs and disclose its threat model. Comparisons against centralized training should be treated as a controlled reference only when lawful pooled data or a synthetic benchmark is available.

This manuscript contributes a detailed mathematical formulation, a flowcharted implementation protocol, a multi-dimensional evaluation matrix, and a worked synthetic numerical illustration. The latter is intentionally separated from empirical evidence. No lender dataset was accessed and no model was trained for this manuscript. The illustrative results demonstrate how future measurements should be organized and interpreted; they do not establish the effectiveness of the proposed system. This distinction protects the scientific validity of the research design and clarifies the experiments required before any deployment claims can be made.

2. Literature Review

Foundational work by McMahan and colleagues introduced communication-efficient federated averaging, in which local stochastic optimization is followed by server-side parameter aggregation. The method demonstrated that decentralized learning can reduce the need to transmit raw training examples, but its original assumptions do not eliminate the effects of skewed client distributions. In financial applications, this issue is especially important because lender portfolios differ substantially in risk composition.

Kairouz and colleagues surveyed advances and unresolved challenges in federated learning, emphasizing statistical heterogeneity, communication constraints, privacy, robustness, and deployment governance. Their synthesis suggests that a financial federation should be evaluated as a system with interacting security and statistical objectives. Performance gains observed on convenient balanced benchmarks may not transfer to real cross-institutional portfolios.

Li and colleagues developed FedProx to improve stability under heterogeneous client data and variable local computation. Its proximal regularizer discourages local models from moving too far from the shared parameters. This approach is relevant when institutions possess dissimilar borrower distributions, but the regularization strength must be tuned carefully: excessive constraint can suppress legitimate local patterns, while insufficient constraint can produce unstable aggregation.

Privacy research shows that the absence of raw-data transfer is not a complete security guarantee. Bonawitz and colleagues proposed practical secure aggregation protocols that allow a server to recover an aggregate while limiting access to individual client updates under a specified adversary model. Such protocols are valuable for banking consortia, although dropout tolerance, collusion assumptions, key management, and implementation overhead require independent assessment.

Differential privacy provides a formal way to bound the effect of individual records on released outputs. Dwork and Roth established the foundational framework, and Abadi and colleagues developed privacy-preserving stochastic-gradient training with gradient clipping and noise. Applied to credit risk, privacy budgets must be interpreted in the context of repeated rounds, sampling design, clipping norms, and the presence of small or rare borrower groups. An epsilon value is not an automatic certification of regulatory compliance.

Attack research has demonstrated the possibility of reconstructing training information from shared gradients in certain settings. Zhu and colleagues examined deep leakage from gradients, highlighting risks that are directly relevant to federated deployments. Financial consortia should therefore test leakage under realistic threat models, including an honest-but-curious coordinator, malicious participants, and auxiliary information held by attackers.

Credit-scoring literature has long emphasized the predictive strength of machine learning alongside challenges in interpretability and governance. Lessmann and colleagues compared classification algorithms for credit scoring and demonstrated the value of rigorous benchmark evaluation. However, many conventional comparisons assume access to centralized data and do not address cross-institution privacy, differential privacy, or institution-specific calibration.

Explainability methods such as SHAP, introduced by Lundberg and Lee, offer a common framework for attributing predictions to input features. In regulated lending, attribution can support model diagnostics and adverse-action analysis, but post hoc explanations require validation for stability and faithfulness. A federated system must also avoid disclosing sensitive client-level information through explanation artifacts or global feature summaries.

Fairness scholarship cautions against treating one metric as a universal definition of equitable outcomes. Hardt and colleagues formalized equality-of-opportunity approaches, while Kleinberg and colleagues demonstrated incompatibilities among some fairness conditions when base rates differ. These findings are particularly salient in multi-lender settings, where default prevalence and customer populations vary. Evaluation should present competing metrics transparently rather than claiming that one numerical score resolves normative questions.

Existing research collectively motivates a layered design: federated optimization for collaborative utility, secure aggregation for update confidentiality, differential privacy for record-level protections, calibration for reliable probabilities, and subgroup evaluation for accountable deployment. The literature does not justify assuming that these layers can be combined without cost. The gap addressed here is a coherent, reproducible protocol for evaluating their interactions in credit-risk prediction across heterogeneous institutions.

3. Research Methodology

3.1 Research design and threat model

The study is structured as a cross-silo, multi-institution experiment. Each participating lender retains its raw borrower records, while a neutral coordinator manages approved model versions and aggregation rounds. The target is a binary default outcome defined by a fixed observation horizon (for example, 90 days past due within 12 months), with definitions harmonized before

training. A common feature dictionary identifies allowable predictors, data types, units, missing-value conventions, and prohibited leakage variables. No personal identifiers leave local sites. The primary threat model assumes an honest-but-curious coordinator and potentially compromised network transport; a separate adversarial evaluation considers malicious or colluding clients. Secure aggregation and differential privacy mitigate different risks and must not be conflated.

3.2 End-to-end workflow

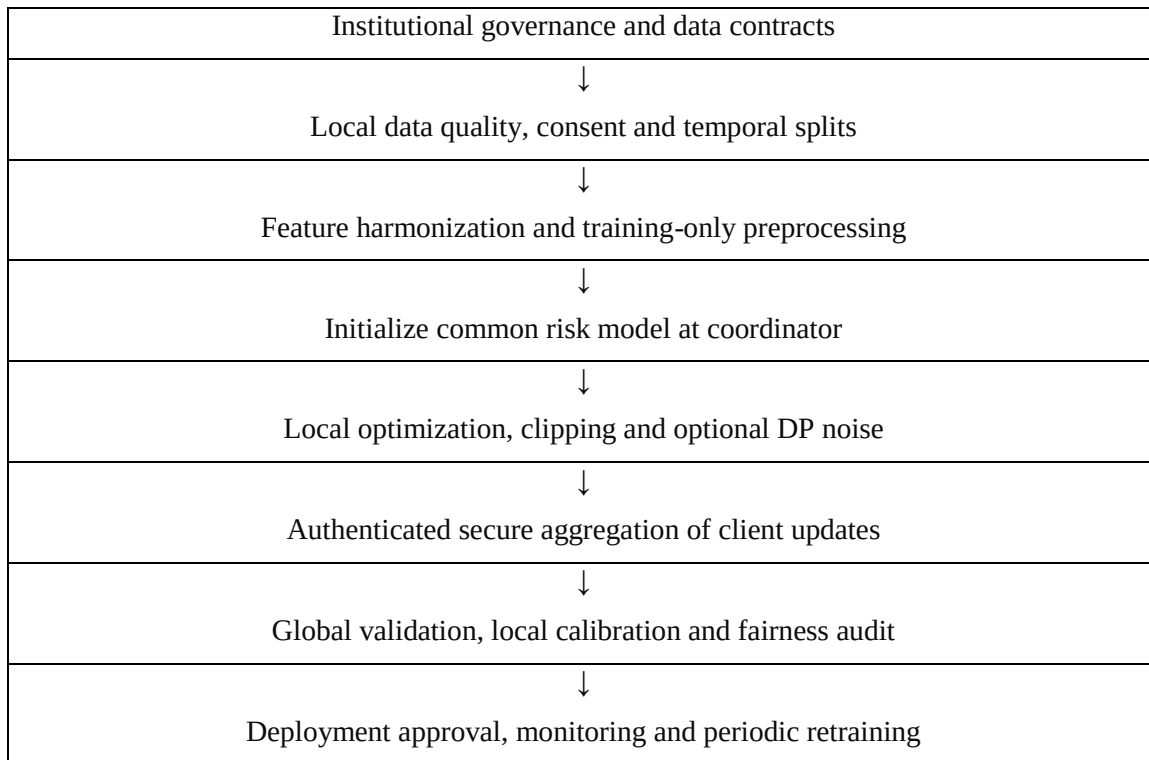


Figure 1. Editable workflow diagram. Each box is a Word table cell and can be modified independently.

3.3 Data partitioning and preprocessing

Partition each institution chronologically into training, validation, and held-out test cohorts, for example 60%, 20%, and 20% by origination date. Maintain an embargo between feature observation and outcome windows to avoid temporal leakage. Fit imputation and scaling only on the training partition at each institution. Encode categorical values through a mutually agreed schema and handle unseen categories explicitly. Track sample counts, class prevalence, feature missingness, and drift without exporting individual records. Exclude post-decision variables, collection outcomes, and other predictors unavailable at underwriting time. For privacy-sensitive audits, share only thresholded aggregate statistics.

3.4 Federated objective and mathematical model

$$F(w) = \sum_k p_k F_k(w)$$

Equation (1): F denotes the global optimization objective; w is the vector of trainable model parameters; k indexes participating institutions; p_k is the nonnegative institution weight, with

weights summing to one; F_k is the empirical loss computed on institution k . Subscript notation uses typographic Unicode characters rather than underscore characters.

$$F_k(w) = (1 / n_k) \sum_i \ell(y_i, f(w, x_i))$$

Equation (2): n_k is the number of local training examples; i indexes local borrowers; x_i represents permitted borrower features; y_i is the binary observed default label; f is the model probability output; and ℓ is a per-example loss function. Cross-entropy is appropriate for binary probability estimation.

$$\ell(y, p) = -y \ln(p) - (1 - y) \ln(1 - p)$$

Equation (3): p is the estimated probability of default and y is the observed binary default indicator. Numerical implementations clip p away from zero and one to avoid undefined logarithms.

$$w_k^{(t+1)} = w^{(t)} - \eta \nabla F_k(w^{(t)})$$

Equation (4): t denotes communication round; η is the local learning rate; ∇F_k is the gradient of institution k 's objective. Multiple local steps may be executed before communicating an update.

$$w^{(t+1)} = \sum_k (n_k / \sum_j n_j) w_k^{(t+1)}$$

Equation (5): the coordinator aggregates eligible local parameter vectors using sample-size weights; j indexes all participating clients in that round. This is the canonical weighted averaging baseline and can be compared with equal-client weighting.

3.5 Heterogeneity-aware optimization

$$G_k(w) = F_k(w) + (\mu / 2) \|w - w^{(t)}\|^2$$

Equation (6): G_k is the local proximal objective; μ controls how strongly the local solution remains near the current global model; $\|\cdot\|$ is the Euclidean norm. Tune μ using only validation data. Client-level performance should be reported so that gains at large lenders do not conceal losses at smaller institutions.

Use a logistic regression model as the transparent reference, a multilayer perceptron as the nonlinear shared model, and a local-only model as the institutional baseline. Hold feature sets, temporal splits, and tuning budgets constant wherever possible. A centralized pooled model may be included only as a lawful reference benchmark or through a fully synthetic shared dataset.

3.6 Secure aggregation and privacy accounting

$$\bar{g} = (1 / m) \sum_i \text{clip}(g_i, C) + N(0, \sigma^2 C^2 I)$$

Equation (7): g_i is a per-example gradient; m is the minibatch size; C is the clipping norm; σ is the noise multiplier; I is the identity matrix; N denotes Gaussian noise. This is a schematic differentially private gradient mechanism; its precise sensitivity, sampling assumptions, and privacy accounting must match the implemented algorithm.

$$\|\text{clip}(g, C)\| \leq C$$

Equation (8): clipping bounds each example's gradient norm by C before adding noise. The privacy accountant tracks the cumulative pair (ϵ, δ) , where ϵ is the privacy-loss parameter and δ is the failure probability. Do not report a numerical privacy guarantee without specifying sampling rate, rounds, clipping, noise and accountant.

Secure aggregation encrypts or masks updates so that the coordinator obtains only a permitted sum after the protocol's dropout and threshold conditions are met. It is implemented in addition to authenticated transport and strict access control. Institution-specific secrets, keys, and raw gradients remain local. A security review should assess client collusion, poisoned updates, membership inference, reconstruction attempts, and availability attacks.

3.7 Calibration, fairness and decision thresholds

$$\text{Brier} = (1 / N) \sum_i (p_i - y_i)^2$$

Equation (9): N is the evaluation sample size; p_i is predicted default probability; y_i is the observed outcome. Lower Brier scores indicate better squared-probability accuracy. Evaluate calibration intercept, calibration slope, and reliability diagrams separately by institution.

$$\text{TPR} = \text{TP} / (\text{TP} + \text{FN})$$

Equation (10): TPR is the true-positive rate; TP is the number of correctly identified defaults; FN is the number of missed defaults. Report false-positive rates and group-level calibration alongside TPR, where group evaluation is legally permissible and sample sizes are adequate.

A fixed decision threshold must be chosen using validation data and a declared cost model, not the held-out test set. Probability calibration can use a local Platt scaling or isotonic mapping fitted only on validation observations. If a shared global threshold is operationally required, disclose differences in institutional approval and error rates. Explanations should use a validated model-specific or post hoc method and be reviewed for stability.

3.8 Experimental protocol and reproducibility

Run at least five random seeds for each configuration and preserve the same temporal splits. Compare local-only, pooled reference where permissible, federated averaging, proximal federation, secure aggregation, and privacy-enhanced federation. Vary client participation rates, data imbalance, default prevalence, communication rounds, and noise levels. Record area under ROC, area under precision-recall curve, Brier score, expected calibration error, recall at a fixed false-positive rate, fairness gaps, wall-clock time, transmitted bytes, and failure rates. Compute confidence intervals by institution-aware bootstrap or repeated independent trials. Release executable configuration files, feature dictionaries, evaluation scripts, and synthetic benchmark generators, subject to institutional policy.

4. Results and Discussion: Synthetic Illustration Only

IMPORTANT: The following figures are constructed hypothetical examples for demonstrating analysis and reporting format. They are not experimental observations, do not imply any training was executed, and must be replaced with measured values before research submission as an empirical study.

Method	ROC AUC	PR AUC	Brier	Illustrative traffic (GB)
Local only	0.752	0.301	0.172	0
Federated averaging	0.793	0.337	0.151	48
Federated proximal	0.806	0.349	0.145	52
Secure aggregation	0.804	0.347	0.146	59
Federated with privacy noise	0.779	0.323	0.158	66

Table 1. Hypothetical model comparison. Higher ROC AUC and PR AUC are better; lower Brier score is better. Traffic is an arbitrary scenario value, not a benchmark.

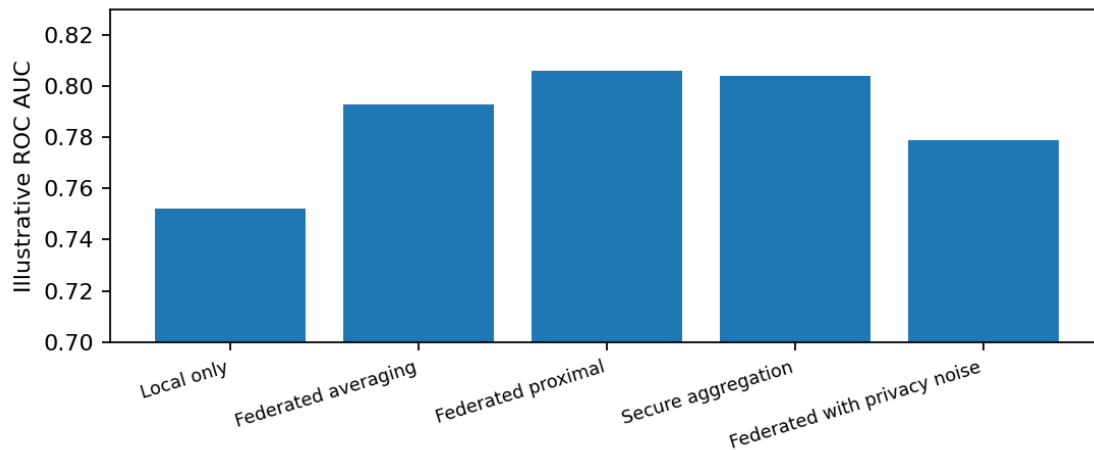


Figure 2. Hypothetical ROC AUC comparison. The illustrative proximal variant exceeds the local-only baseline by 0.054 AUC points. This arithmetic difference is not a statistically verified improvement. The privacy-enhanced variant illustrates a possible utility cost of added noise.

Illustrative institution	Default prevalence	Local AUC	Federated AUC
A	0.05	0.76	0.8
B	0.11	0.74	0.79
C	0.18	0.71	0.78
D	0.08	0.77	0.81

Table 2. Hypothetical client heterogeneity. Differences in prevalence imply that a single aggregate discrimination score may mask institutional performance and calibration differences.

Scenario	Illustrative ϵ	ROC AUC	Brier
No DP	Not applicable	0.806	0.145
Stronger noise	Illustrative 3	0.771	0.164
Moderate noise	Illustrative 8	0.786	0.154

Table 3. Hypothetical privacy-utility sensitivity. The epsilon labels are conceptual placeholders and are not computed privacy guarantees. A real study must publish accountant assumptions and actual computed epsilon values.

Interpretation requires attention to both operational and statistical validity. A higher aggregate ROC AUC does not ensure better decisions at a lender’s actual approval threshold. The example Brier values suggest a calibration benefit in the hypothetical proximal condition, but genuine conclusions would require calibration plots and uncertainty intervals. Likewise, traffic volumes alone cannot establish cost efficiency without measured message sizes, bandwidth, client dropouts, and encryption overhead.

The illustrative privacy comparison emphasizes that noise can trade predictive utility for record-level protection. However, privacy strength cannot be inferred from noise labels or from the absence of raw-data transmission. A real evaluation should estimate membership-inference advantage, validate aggregation threshold behavior, and document accountant outputs. Fairness analysis must report subgroup sample sizes, uncertainty, and legal constraints. No causal fairness or compliance claim is warranted by the constructed tables.

5. Limitations, Ethics and Deployment Considerations

The proposed architecture remains unvalidated until it is tested on authorized multi-institution data or a transparent public benchmark. Potential threats include inconsistent default definitions, selective labels caused by earlier credit approvals, temporal leakage, nonrandom missingness, model inversion, poisoned updates, and distribution shift. Differential privacy and secure aggregation do not eliminate these risks. Deployment would require legal review, explicit institutional agreements, audit logs, change management, human oversight, and monitoring for disparate impacts. The synthetic numerical scenarios are unsuitable for supporting performance or regulatory claims.

6. Conclusion

This paper develops a detailed federated credit-risk assessment framework that integrates heterogeneous-client optimization, secure aggregation, optional record-level differential privacy, institution-aware calibration, and fairness-oriented monitoring. Its central contribution is a reproducible research design that treats privacy, predictive quality, governance, and operational feasibility as jointly necessary objectives. Mathematical formulations and workflow stages clarify the implementation requirements, while the synthetic numerical examples illustrate appropriate comparative reporting without misrepresenting hypothetical values as evidence. Future work should conduct authorized multi-lender experiments, quantify uncertainty across institutions and

economic cycles, validate privacy accounting and leakage resistance, and evaluate real-world decision costs before operational adoption.

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