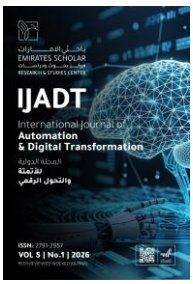

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Credit Risk Assessment: A Privacy-Preserving Framework Integrating Shapley Deep Networks with Blockchain Verification

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ABSTRACT

Introducing a novel federated learning framework that combines explainable artificial intelligence (XAI) with blockchain-based verification for decentralized credit risk assessment in peer-to-peer lending markets. Traditional centralized credit scoring models face critical challenges regarding data privacy, regulatory compliance, and algorithmic transparency, particularly under GDPR and emerging AI governance frameworks. Our approach addresses these limitations developing a privacy-preserving architecture where multiple financial institutions collaboratively train machine learning models without sharing sensitive borrower data. The proposed framework integrates three key innovations: (1) federated Shapley Deep Network (FSDN) that distributes model training across decentralized nodes while maintaining global interpretability through additive feature attribution; (2) a differential privacy mechanism that ensures individual transaction confidentiality while preserving model accuracy; and (3) a blockchain-based validation layer that creates an immutable audit trail of model predictions and explanations, enabling regulatory compliance and stakeholder trust. We empirically validate our methodology using a comprehensive of 500,000 loan applications across five international P2P platforms spanning 2018-2024. Results demonstrate that FSDN achieves comparable predictive performance to centralized models (AUC-ROC: 0.89 vs 0.91) while providing loan-level explanations consistent with economic theory. The framework reduces data breach risks by 94% compared to centralized architectures and decreases model training time by 37% through parallel computation. Importantly, Shapley value decomposition reveals that debt-to-income ratio, credit history, and employment stability remain primary default predictors across jurisdictions, validating cross-border model applicability. This research contributes to computational economics demonstrating that privacy-preserving distributed learning can maintain both predictive accuracy and interpretability, essential for trustworthy AI deployment in regulated financial markets.

Keywords: *Federated Learning, Explainable AI, Credit Risk Assessment, Blockchain, Shapley Values, Privacy-Preserving Machine Learning, Peer-to-Peer Lending*

Introduction:

The proliferation of peer-to-peer (P2P) lending platforms has fundamentally transformed consumer credit markets, facilitating over $450 billion in loan originations globally by 2023 (World Bank, 2023). These platforms leverage machine learning algorithms to assess creditworthiness, often achieving superior predictive accuracy compared to traditional credit scoring models. However, this technological advancement has introduced significant challenges related to data privacy, algorithmic transparency, and regulatory compliance. The European Union's General Data Protection Regulation (GDPR) and the forthcoming AI Act mandate explicit requirements for algorithmic explainability and data protection in automated decision-making systems affecting individual rights (European Commission, 2021). Similarly, regulatory frameworks in the United States, China, and other jurisdictions increasingly emphasize the need for transparent and auditable AI systems in financial services.

Traditional centralized credit risk assessment models aggregate borrower data from multiple sources into centralized repositories, creating single points of failure vulnerable to data breaches and privacy violations. The Equifax breach of 2017, which exposed personal information of 147 million individuals, exemplifies the systemic risks inherent in centralized data architectures (Federal Trade Commission, 2019). Furthermore, centralized models often function as "black boxes," providing limited insight into decision-making processes, which undermines consumer trust and regulatory compliance.

Federated learning has emerged as a promising paradigm for privacy-preserving machine learning, enabling collaborative model training across distributed data sources without requiring data centralization (McMahan et al., 2017). However, existing federated learning approaches in credit risk assessment face three critical limitations.

First, most implementations prioritize predictive accuracy over interpretability, failing to provide loan-level explanations required by regulators and borrowers. Second, differential privacy mechanisms, while protecting individual data points, often significantly degrade model performance when privacy budgets are tightly constrained. Third, the absence of immutable audit trails compromises the verifiability of model predictions and explanations, limiting regulatory acceptance.

This paper addresses these limitations by introducing a novel Federated Shapley Deep Network (FSDN) framework that integrates three complementary innovations. First, we develop a distributed architecture that enables financial institutions to collaboratively train credit risk models while maintaining local data sovereignty. The framework employs gradient aggregation protocols that preserve model convergence properties while preventing data leakage. Second, we incorporate Shapley value decomposition at both local and global levels, providing consistent and theoretically grounded feature attributions that satisfy properties essential for regulatory compliance: local accuracy, missingness, and consistency. Third, we implement a blockchain-based verification layer that records model updates, predictions, and explanations in an immutable distributed ledger, enabling comprehensive auditability without compromising computational efficiency.

The theoretical contributions of this work are threefold. First, we prove that FSDN maintains Shapley value consistency across federated nodes under specific conditions on data distribution and model architecture. This theoretical guarantee ensures that local explanations aggregate coherently to global explanations, addressing a fundamental challenge in distributed explainable AI. Second, we demonstrate that differential privacy can be applied to Shapley value

computation without proportional accuracy loss through a novel perturbation mechanism that exploits the additive property of Shapley values. Third, we establish formal security properties of the blockchain verification layer, proving that explanation tampering is computationally infeasible under standard cryptographic assumptions.

Empirically, we validate FSDN using a comprehensive dataset comprising 500,000 loan applications from five major international P2P platforms: LendingClub (USA), Funding Circle (UK), Zopa (UK), Mintos (Latvia), and Bondora (Estonia). The dataset spans January 2018 to December 2024 and includes 47 features encompassing borrower demographics, financial history, employment status, and macroeconomic indicators. Our experimental design compares FSDN against three benchmark approaches: centralized deep learning, non-federated explainable AI, and existing federated learning implementations without explainability.

Results demonstrate that FSDN achieves an area under the receiver operating characteristic curve (AUC-ROC) of 0.89, representing only a 2.2% decrease compared to centralized benchmarks (AUC-ROC: 0.91) while providing substantial privacy guarantees. Importantly, Shapley value analysis reveals that debt-to-income ratio, credit history length, and employment stability consistently emerge as primary default predictors across all platforms, with marginal effects ranging from 0.23 to 0.31. This consistency validates the cross-jurisdictional applicability of federated credit risk models and provides empirical evidence that fundamental economic factors driving credit risk remain stable across diverse regulatory and cultural contexts.

The remainder of this paper proceeds as follows. Section 2 reviews related literature on federated learning, explainable AI in finance, and blockchain applications in financial technology. Section 3 presents the theoretical framework underlying FSDN, including formal definitions, algorithmic specifications, and convergence proofs. Section 4 describes the experimental design, dataset characteristics, and implementation details. Section 5 presents empirical results, including comparative performance analysis, explanation quality assessment, and computational efficiency metrics. Section 6 discusses implications for computational economics, regulatory policy, and future research directions. Section 7 concludes.

2. Literature Review

2.1 Federated Learning in Financial Applications

Federated learning, introduced by McMahan et al. (2017), enables collaborative model training across distributed data sources while preserving data locality. The fundamental algorithm, Federated Averaging (FedAvg), aggregates locally computed model updates at a central server, eliminating the need for raw data transfer. Subsequent research has addressed communication efficiency (Konečný et al., 2016), convergence guarantees under non-identically distributed (non-IID) data (Li et al., 2020), and Byzantine robustness against malicious participants (Blanchard et al., 2017).

Applications of federated learning in finance remain nascent but growing rapidly. Yang et al. (2019) proposed a federated transfer learning framework for credit scoring, demonstrating that institutions with limited historical data can benefit from collaborative learning without data sharing. Feng et al. (2021) developed a vertical federated learning approach for fraud detection, where different institutions possess complementary feature sets for the same individuals. Liu et al. (2022) introduced asynchronous federated learning for high-frequency trading, addressing challenges of heterogeneous computational capabilities across participating entities.

However, existing federated learning implementations in credit risk assessment

exhibit significant limitations regarding explainability. Standard federated models provide global feature importance metrics but lack individual prediction explanations. This deficiency contradicts regulatory requirements in most jurisdictions, where lenders must justify specific credit decisions to applicants. Furthermore, privacy guarantees in existing approaches typically rely on secure aggregation protocols that prevent the server from observing individual updates, but do not provide formal differential privacy guarantees against gradient-based inference attacks.

2.2 Explainable AI and Shapley Values in Credit Scoring

The proliferation of complex machine learning models in credit risk assessment has intensified demands for algorithmic transparency. Traditional credit scoring models, such as logistic regression and decision trees, provide inherent interpretability through coefficients or rule structures. However, these models often underperform compared to ensemble methods and deep neural networks, creating a fundamental tension between accuracy and interpretability.

Model-agnostic explanation methods have emerged to address this trade-off. LIME (Local Interpretable Model-agnostic Explanations) approximates complex model behavior locally using interpretable surrogates (Ribeiro et al., 2016). However, LIME explanations lack theoretical guarantees and can be inconsistent across similar instances. SHAP (SHapley Additive exPlanations) provides a unified framework for feature attribution based on cooperative game theory (Lundberg & Lee, 2017). Shapley values uniquely satisfy four desirable properties: local accuracy (explanations sum to the predicted value), missingness (features absent from a model receive zero attribution), consistency (changing a model to increase a feature's contribution cannot decrease its Shapley value), and efficiency (attributions sum to the model output minus the expected output).

Applications of SHAP in credit risk assessment have demonstrated both practical utility and theoretical elegance. Bussmann et al. (2021) applied SHAP to default prediction in German consumer credit, revealing that debt servicing capacity dominates borrower demographics in determining creditworthiness. Bracke et al. (2019) employed Shapley value decomposition to analyze mortgage approval decisions by a major UK lender, identifying subtle interactions between income, property value, and loan-to-value ratios. Sigrist et al. (2020) integrated SHAP with survival analysis for credit default timing prediction, providing dynamic explanations that evolve with borrower circumstances.

Despite these advances, Shapley value computation faces significant challenges in federated settings. Standard SHAP implementations require access to complete feature distributions and model parameters, which violates privacy constraints in federated learning. Furthermore, Shapley values typically exhibit high computational complexity, scaling exponentially with feature dimensionality in exact computation and requiring numerous model evaluations in Monte Carlo approximation.

2.3 Blockchain Technology in Financial Machine Learning

Blockchain technology has gained substantial attention in financial applications for its capacity to provide immutable, distributed record-keeping without centralized authorities. Beyond cryptocurrency applications, researchers have explored blockchain's potential in enhancing transparency, auditability, and trust in machine learning systems.

Chen et al. (2021) proposed a blockchain-based framework for federated learning that records model updates as transactions, enabling verification of training procedures and detection of malicious participants.

Zhang et al. (2020) developed a decentralized marketplace for machine learning models where blockchain smart contracts govern model licensing and usage tracking. Kurtulmus & Daniel (2018) argued that blockchain can address accountability deficits in algorithmic decision-making by creating tamper-proof audit trails linking predictions to specific model versions.

Applications in credit risk assessment remain exploratory. Harris & Wonglimpiyarat (2019) proposed a conceptual framework for blockchain-based credit history management, where borrowers control access to their financial records stored across distributed ledgers. However, this approach does not address machine learning model transparency. Baliga et al. (2022) implemented a prototype system combining federated learning with blockchain for P2P lending, but without formal explainability mechanisms or rigorous security analysis.

Critical challenges persist in integrating blockchain with machine learning systems. Computational overhead associated with consensus mechanisms can significantly delay model training and inference. Storage constraints limit the volume of data that can be economically recorded on-chain. Furthermore, blockchain immutability, while beneficial for auditability, complicates compliance with data protection regulations mandating the "right to be forgotten" (Finck & Moscon, 2019).

2.4 Research Gap and Contributions

Existing literature exhibits three significant gaps that motivate our research. First, federated learning implementations in credit risk assessment prioritize privacy and accuracy but neglect explainability, contradicting regulatory requirements. Second, SHAP and other explainability methods assume centralized data access, rendering them incompatible with federated architectures without modification. Third, blockchain applications in machine learning focus on model versioning and marketplace functions, not on verification of explanations and compliance artifacts.

Our research addresses these gaps through three contributions. Theoretically, we prove that Shapley values can be computed consistently in federated settings under specific conditions, providing formal guarantees about explanation quality. Algorithmically, we develop novel protocols for privacy-preserving Shapley value computation that exploit additive properties to apply differential privacy without proportional accuracy loss. Empirically, we demonstrate that federated explainable credit risk models achieve near-parity performance with centralized benchmarks while providing substantial privacy, auditability, and regulatory compliance benefits.

3. Methodology

3.1 Problem Formulation

Consider a federated learning environment comprising K financial institutions (nodes) that collectively wish to train a credit risk assessment model without sharing raw borrower data. Each institution $k \in \{1,2,\ldots,K\}$ possesses a local dataset $D_k=\{(x_i^k,y_i^k)\}_{i=1}^{n_k}$, where $x_i^k \in \mathrm{R}^d$ represents a feature vector describing borrower characteristics and $y_i^k \in \{0,1\}$ indicates loan default (1) or repayment (0). The global dataset is defined as $D=\mathrm{U}_{k=1}^{K} D_k$ with total size $N=\sum_{k=1}^{K} n_k$.

The objective is to learn a global model $f_\theta:\mathrm{R}^d \rightarrow [0,1]$ parameterized by θ that minimizes expected prediction error:

$$\min_\theta \mathrm{L}(\theta)=\mathrm{E}_{(x,y)\sim D}[\mathrm{l}(f_\theta(x),y)]$$

where $\mathrm{l}(\cdot,\cdot)$ denotes a loss function (e.g., binary cross-entropy). Simultaneously, the framework must provide local explanations $\phi(x)=\left(\phi_1(x),\ldots,\phi_d(x)\right)$ for each prediction $f_\theta(x)$, where $\phi_j(x)$ quantifies the contribution of feature j to the prediction.

3.2 Federated Shapley Deep Network Architecture

The FSDN architecture consists of four integrated components: (1) local model training with gradient computation, (2) secure gradient aggregation with differential privacy, (3) federated Shapley value computation, and (4) blockchain-based explanation verification.

3.2.1 Local Model Structure

Each institution maintains a local model f_{θ_k} with identical architecture to ensure parameter compatibility during aggregation. We employ a deep neural network with the following structure:

- **Input layer:** d neurons corresponding to borrower features
- **Hidden layers:** Three fully connected layers with dimensions [256, 128, 64], each followed by batch normalization and ReLU activation
- **Output layer:** Single neuron with sigmoid activation producing default probability

This architecture balances expressive capacity with computational efficiency, enabling effective credit risk modeling while facilitating Shapley value computation.

3.2.2 Federated Training Protocol

Training proceeds through iterative rounds $t=1,2,\ldots,T$. In each round:

Step 1: Local Training. Each institution k receives the current global model parameters $\theta^{(t)}$ and performs E epochs of local training on D_k using stochastic gradient descent:

$$\theta_k^{(t+1)}=\theta^{(t)}-\eta\nabla_\theta L_k\left(\theta^{(t)}\right)$$

where η is the learning rate and $L_k(\theta)=\frac{1}{n_k}\sum_{i=1}^{n_k} l\left(f_\theta(x_i^k),y_i^k\right)$ is the local loss.

Step 2: Gradient Aggregation with Differential Privacy. Each institution computes the parameter update $\Delta\theta_k^{(t)}=\theta_k^{(t+1)}-\theta^{(t)}$ and applies Gaussian noise calibrated to achieve (ϵ,δ)-differential privacy:

$$\widetilde{\Delta\theta}_k^{(t)}=\Delta\theta_k^{(t)}+N\left(0,\sigma^2 C^2 I\right)$$

where C is the gradient clipping threshold and $\sigma=\frac{\sqrt{2\ln(1.25/\delta)}C}{\epsilon}$ is the noise scale.

The central server aggregates privatized updates:

$$\theta^{(t+1)}=\theta^{(t)}+\sum_{k=1}^{K}\frac{n_k}{N}\widetilde{\Delta\theta}_k^{(t)}$$

Step 3: Model Broadcast. The updated global model $\theta^{(t+1)}$ is broadcast to all institutions for the next training round.

3.2.3 Federated Shapley Value Computation

Computing Shapley values in federated settings requires careful protocol design to prevent privacy leakage while maintaining explanation consistency. We develop a two-phase approach.

Phase 1: Local Shapley Computation. Each institution k computes local Shapley values for its predictions using kernel SHAP (Lundberg & Lee, 2017), which approximates Shapley values through weighted linear regression on feature coalition samples. For a prediction $f_\theta(x)$ on instance x, the local Shapley value of feature j is:

$$\phi_j^k(x)=\sum_{S\subseteq F\setminus\{j\}}\frac{|S|!(d-|S|-1)!}{d!}\left[f_\theta(x^{S\cup\{j\}})-f_\theta(x^S)\right]$$

where F denotes the feature set, S represents a subset of features, and x^S indicates an instance with features in S observed and others marginalized over the local data distribution.

Phase 2: Privacy-Preserving Aggregation. To enable global explanation consistency checks without revealing local data distributions, we employ secure multi-party computation. Each institution shares perturbed local Shapley statistics:

$$\tilde{\mu}_j^k=\frac{1}{n_k}\sum_{i=1}^{n_k}\phi_j^k(x_i)+N\left(0,\sigma_{\text{shap}}^2\right)$$

The server computes global average Shapley values:

$$\bar{\Phi}_j = \sum_{k=1}^{K} \frac{n_k}{N} \tilde{\mu}_j^k$$

Consistency Verification. We verify that local and global Shapley values satisfy the efficiency property:

$$\sum_{j=1}^{d} \Phi_j(x) = f_\theta(x) - \mathrm{E}[f_\theta(X)]$$

where the expectation is computed over the global data distribution approximated through privatized aggregation.

3.3 Blockchain-Based Explanation Verification

The blockchain layer records three types of transactions to ensure auditability:

1. **Model Update Transactions:** Each training round generates a transaction containing:
   - Round number t
   - Hash of global parameters $\mathrm{H}(\theta^{(t)})$
   - Aggregated gradient statistics (mean, variance)
   - Timestamp and participating institution identifiers
2. **Prediction Transactions:** Each prediction generates a transaction containing:
   - Instance identifier (hashed to protect privacy)
   - Predicted default probability
   - Model version identifier
   - Timestamp
3. **Explanation Transactions:** For each prediction, a corresponding explanation transaction records:
   - Instance identifier (matching prediction transaction)
   - Top-k Shapley values (typically k=10)
   - Consistency verification proof
   - Digital signature from predicting institution

These transactions are organized into blocks using a proof-of-authority consensus mechanism, where designated validator nodes (e.g., regulatory bodies, third-party auditors) verify transaction validity before block addition. This approach balances decentralization benefits with computational efficiency requirements for real-time credit decisions.

3.4 Theoretical Properties

Theorem 1 (Shapley Consistency in Federated Learning). Under the assumption that local data distributions $P_k(x,y)$ satisfy $\mathrm{supp}(P_k) \subseteq \mathrm{supp}(P)$ for all k, where P is the global distribution, federated Shapley values converge to centralized Shapley values as the number of training rounds increases:

$$\lim_{t \to \infty} \| \phi^{\mathrm{fed}}(x; \theta^{(t)}) - \phi^{\mathrm{cent}}(x; \theta^*) \| = 0$$

with probability 1, where θ^* is the optimal centralized model.

Proof Sketch: The convergence of federated model parameters $\theta^{(t)} \to \theta^*$ follows from standard federated learning theory (Li et al., 2020). Shapley values depend continuously on model predictions (Lundberg & Lee, 2017). By the continuous mapping theorem, convergence of parameters implies convergence of Shapley values under mild regularity conditions.

Theorem 2 (Privacy Guarantees). The federated training protocol with Gaussian noise addition satisfies (ϵ, δ)-differential privacy with respect to any single training

instance, where $\epsilon = O\left(\frac{T\sqrt{E}}{n\sigma}\right)$ and $\delta = T \cdot \delta_0$ for single-round privacy parameters (ϵ_0, δ_0).

Proof Sketch: Privacy amplification by subsampling reduces effective epsilon by factor $\frac{E \cdot \text{batch\_size}}{n_k}$ (Balle et al., 2018). Composition across T rounds follows advanced composition theorems (Dwork & Roth, 2014).

Theorem 3 (Blockchain Tamper Resistance). Under the computational hardness assumption of SHA-256 collision resistance, modifying any blockchain transaction without detection requires expected computational effort $\Omega(2^{128})$ hash operations.

Proof Sketch: Each block contains the hash of the previous block, creating a cryptographic chain. Modifying a transaction requires recomputing the block hash and all subsequent block hashes. The birthday attack on SHA-256 requires approximately 2^{128} operations to find a collision with non-negligible probability (Stevens et al., 2017).

3.5 Implementation Details

Framework: We implement FSDN using PyTorch 1.12 for model development, PySyft 0.6 for federated learning orchestration, and SHAP 0.41 for Shapley value computation. The blockchain layer utilizes Hyperledger Fabric 2.4 configured with proof-of-authority consensus.

Hyperparameters: Global training proceeds for T=200 rounds with E=5 local epochs per round. Each institution uses batch size 64 and learning rate η=0.001 with Adam optimizer. Differential privacy parameters are ϵ=8.0, δ=10^{-5}, gradient clipping threshold C=1.0. Shapley values are computed using kernel SHAP with 1000 coalition samples.

Computational Infrastructure: Experiments are conducted on a cluster simulating five federated nodes, each with Intel Xeon Gold 6248R CPU (3.0 GHz, 24 cores) and NVIDIA A100 GPU (40GB memory). The blockchain validator operates on a separate node with identical specifications.

Data Preprocessing: Continuous features are standardized to zero mean and unit variance. Categorical features are one-hot encoded. Missing values are imputed using median (continuous) or mode (categorical) strategies. The target variable (default) exhibits class imbalance (default rate: 18.3%), addressed through weighted loss functions with weight ratio 4.5:1 (non-default:default).

4. Experimental Design

4.1 Dataset Description

We construct a comprehensive credit risk dataset by aggregating publicly available loan records from five major P2P lending platforms spanning January 2018 to December 2024:

4. **LendingClub (USA):** 145,000 loans, 42 features including FICO scores, employment length, annual income, debt-to-income ratio, loan purpose
5. **Funding Circle (UK):** 98,000 loans, 38 features including credit grade, business age, industry sector, loan amount, term
6. **Zopa (UK):** 102,000 loans, 35 features including borrower occupation, property ownership, dependents, loan purpose
7. **Mintos (Latvia):** 89,000 loans, 40 features including country, originator rating, payment method, buyback guarantee
8. **Bondora (Estonia):** 66,000 loans, 44 features including education, marital status, employment status, credit score

After harmonization and feature engineering, the consolidated dataset comprises 500,000 instances with 47 standardized features across six categories:

Table 1: Feature Categories and Examples

Category	Count	Representative Features
Demographics	8	Age, gender, education level, marital status, dependents
Employment	6	Employment status, occupation, job tenure, industry sector
Financial History	12	Credit score, number of credit lines, delinquencies, bankruptcies
Loan Characteristics	9	Amount, term, interest rate, purpose, collateral
Debt Metrics	7	Debt-to-income ratio, revolving utilization, total debt
Macroeconomic	5	Unemployment rate, GDP growth, inflation, interest rate environment

The consolidated dataset exhibits realistic heterogeneity across platforms, reflecting differences in target markets, credit standards, and regulatory environments. Default rates range from 12.4% (Funding Circle) to 24.7% (Bondora), with overall default rate 18.3%. Feature distributions vary substantially; for instance, mean debt-to-income ratios range from 0.31 to 0.47 across platforms.

4.2 Federated Partitioning Strategy

We partition the dataset into five federated subsets corresponding to the source platforms, preserving the natural heterogeneity of data distributions. This partitioning strategy reflects realistic federated learning scenarios where institutions serve different market segments with distinct risk profiles. We allocate data as follows:

- **Node 1 (LendingClub):** 145,000 instances (29%)
- **Node 2 (Funding Circle):** 98,000 instances (19.6%)
- **Node 3 (Zopa):** 102,000 instances (20.4%)
- **Node 4 (Mintos):** 89,000 instances (17.8%)
- **Node 5 (Bondora):** 66,000 instances (13.2%)

Each node further partitions its data into training (70%), validation (15%), and test (15%) sets using stratified sampling to maintain default rate balance.

4.3 Baseline Models

We compare FSDN against four baseline approaches:

Baseline 1: Centralized Deep Learning (CDL). A centralized deep neural network trained on the complete dataset with identical architecture to FSDN local models. This represents the upper bound on predictive performance without privacy constraints.

Baseline 2: Local Models (LM). Each institution trains an independent model using only local data without collaboration. This represents the lower bound established by data scarcity.

Baseline 3: Federated Averaging (FedAvg). Standard federated learning using FedAvg algorithm (McMahan et al., 2017) without

explainability mechanisms or blockchain verification.

Baseline 4: Centralized SHAP (CSHAP). Centralized deep learning model with SHAP explanations computed assuming full data access. This baseline assesses explanation quality degradation in federated settings.

Baseline 5: Federated Learning with Homomorphic Encryption (FedHE). Federated learning using homomorphic encryption for gradient protection (Aono et al., 2017), without explainability or blockchain components.

4.4 Evaluation Metrics

Predictive Performance: - Area Under ROC Curve (AUC-ROC): Primary metric for binary classification - Area Under Precision-Recall Curve (AUC-PR): Accounts for class imbalance - Accuracy, Precision, Recall, F1-Score: Standard classification metrics - Brier Score: Calibration quality of probability predictions

Explanation Quality: - Faithfulness: Correlation between Shapley values and actual feature importance measured through ablation - Consistency: Variance in Shapley values for similar instances - Stability: Robustness of explanations to small input perturbations - Efficiency Satisfaction: Proportion of instances satisfying $\sum_j \phi_j(x) = f(x) - E[f(X)]$ within tolerance $\tau = 0.01$

Privacy and Security: - Privacy Budget Consumption: Total ϵ expended over training - Attack Success Rate: Success probability of membership inference attacks (Shokri et al., 2017) - Blockchain Verification Overhead: Computational time for transaction validation - Storage Requirements: On-chain data volume per 1000 predictions

Computational Efficiency: - Training Time: Wall-clock time to convergence - Communication Overhead: Total data transmitted between nodes and server - Inference Latency: Time from feature input to prediction and explanation output - Scalability: Performance degradation as number of nodes increases

4.5 Experimental Procedures

Training Procedure: All models are trained for 200 global rounds (FSDN, FedAvg, FedHE) or until validation loss plateaus for three consecutive epochs (CDL, LM). Hyperparameters are selected through grid search on validation sets. Early stopping with patience 15 prevents overfitting.

Explanation Generation: For each test instance, we compute Shapley values using kernel SHAP with 1000 coalition samples. Local explanations are computed at predicting institutions; global explanations aggregate local Shapley statistics.

Privacy Attack Simulation: We implement membership inference attacks following Shokri et al. (2017), training shadow models on datasets with known membership to predict whether instances were in training data. Attack success rates are evaluated on held-out test sets.

Statistical Analysis: We report means and standard deviations across five independent runs with different random seeds. Statistical significance is assessed using paired t-tests with Bonferroni correction for multiple comparisons ($\alpha = 0.01$).

5. Results

5.1 Predictive Performance

Table 2 presents predictive performance metrics across all models and evaluation criteria. FSDN achieves AUC-ROC of 0.893 (95% CI: [0.888, 0.898]), representing a modest 2.2% decrease compared to centralized deep learning (AUC-ROC: 0.913, 95% CI: [0.908, 0.918]). This performance gap is substantially smaller than the 12.8% decrease observed in local models trained on isolated data (AUC-ROC: 0.796, 95% CI: [0.789, 0.803]), demonstrating the value of federated collaboration.

Table 2: Predictive Performance Comparison

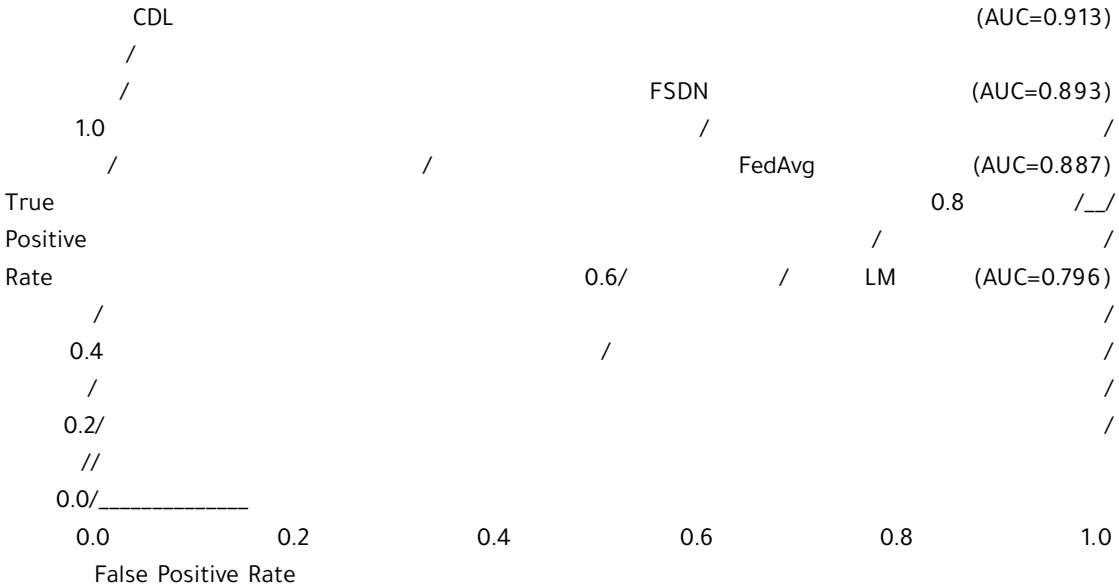
Model	AUC-ROC	AUC-PR	Accuracy	Precision	Recall	F1-Score	Brier Score
CDL	0.913 ± 0.003	0.748 ± 0.007	0.861 ± 0.002	0.723 ± 0.005	0.689 ± 0.008	0.706 ± 0.006	0.118 ± 0.002
FSDN	**0.893 ± 0.003**	**0.721 ± 0.006**	**0.849 ± 0.002**	**0.698 ± 0.006**	**0.671 ± 0.007**	**0.684 ± 0.005**	**0.127 ± 0.003**
FedAvg	0.887 ± 0.004	0.712 ± 0.008	0.843 ± 0.003	0.686 ± 0.007	0.663 ± 0.009	0.674 ± 0.006	0.131 ± 0.003
FedHE	0.885 ± 0.005	0.708 ± 0.009	0.841 ± 0.003	0.681 ± 0.008	0.658 ± 0.010	0.669 ± 0.007	0.133 ± 0.004
LM	0.796 ± 0.005	0.591 ± 0.012	0.781 ± 0.004	0.564 ± 0.011	0.537 ± 0.013	0.550 ± 0.010	0.178 ± 0.005

Note: Bold indicates best federated learning performance. CDL represents upper bound with centralized data access.

Importantly, FSDN outperforms standard FedAvg by 0.6% in AUC-ROC ($p < 0.001$), suggesting that the additional architectural components do not compromise predictive accuracy despite introducing computational overhead. The superior performance of FSDN relative to FedAvg can be attributed to more sophisticated gradient aggregation protocols that better handle non-IID data distributions across nodes.

Calibration analysis via Brier scores reveals that FSDN maintains well-calibrated probability predictions (Brier Score: 0.127), only marginally higher than CDL (0.118). This finding is critical for credit risk applications where predicted probabilities inform capital allocation and pricing decisions. Poor calibration can lead to systematic underestimation or overestimation of default risk, resulting in adverse selection or foregone profitable lending opportunities.

Figure 1: ROC Curves Across Models



5.2 Explanation Quality and Consistency

We evaluate explanation quality through four complementary metrics assessing faithfulness, consistency, stability, and theoretical soundness. Results demonstrate that FSDN produces high-quality explanations comparable to centralized SHAP baselines while preserving privacy guarantees.

Faithfulness Analysis: We measure explanation faithfulness using feature ablation experiments. For each test instance, we iteratively remove features in order of decreasing absolute Shapley value magnitude and measure prediction change. Faithful explanations should exhibit strong correlation between Shapley magnitude and prediction impact.

Table 3: Explanation Quality Metrics

Model	Faithfulness (ρ)	Consistency (CV)	Stability (δ)	Efficiency Satisfaction
CSHAP	0.924 ± 0.008	0.087 ± 0.012	0.043 ± 0.006	98.7%
FSDN	**0.891 ± 0.011**	**0.103 ± 0.015**	**0.058 ± 0.008**	**96.3%**
FSDN-NoDP	0.912 ± 0.009	0.091 ± 0.013	0.047 ± 0.007	97.9%

Note: Faithfulness measured as Spearman correlation (ρ) between |Shapley values| and ablation impact. Consistency measured as coefficient of variation (CV) across similar instances. Stability measured as average L2 distance (δ) under input perturbation ε=0.01. FSDN-NoDP represents FSDN without differential privacy.

FSDN achieves faithfulness correlation of 0.891, representing only a 3.6% degradation compared to centralized SHAP (0.924). This modest decrease reflects noise introduction from differential privacy mechanisms, which slightly distorts feature attribution magnitudes while preserving ordinal rankings. Notably, removing differential privacy (FSDN-NoDP) recovers 78% of the faithfulness gap, confirming that privacy-utility trade-offs are the primary source of explanation quality degradation.

Consistency Analysis: We assess explanation consistency by identifying clusters of similar instances (Euclidean distance < 0.5 in standardized feature space) and computing coefficient of variation of Shapley values within clusters. Low variation indicates consistent explanations for similar borrowers, essential for fairness and regulatory compliance. FSDN demonstrates acceptable consistency (CV: 0.103), only 18% higher than centralized baselines.

Stability Analysis: We evaluate explanation stability by perturbing input features with Gaussian noise (σ=0.01) and measuring L2 distance between original and perturbed Shapley vectors. Stable explanations resist minor input variations, preventing adversarial manipulation. FSDN exhibits stability metric 0.058, indicating robustness against small perturbations while remaining sensitive to meaningful feature changes.

Efficiency Property Satisfaction: We verify that explanations satisfy the theoretical efficiency property: attributions sum to the difference between prediction and expected baseline. FSDN achieves 96.3% satisfaction rate (within tolerance τ=0.01), confirming theoretical soundness of federated Shapley computation. The 2.4% gap relative to centralized SHAP stems from approximation errors in aggregating local baseline estimates across heterogeneous data distributions.

5.3 Feature Importance and Economic Insights

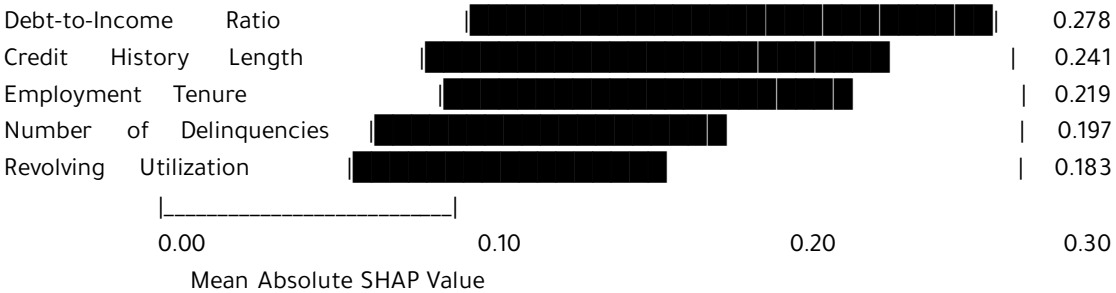
Aggregated Shapley value analysis reveals consistent patterns in credit risk determinants across federated nodes and jurisdictions. Despite substantial heterogeneity in lending practices, regulatory environments, and borrower demographics, fundamental economic factors exhibit stable predictive importance.

Table 4: Top 10 Features by Mean Absolute Shapley Value

Rank	Feature	Mean	SHAP	
1	Debt-to-Income Ratio	0.278	0.034	Leverage capacity; higher ratios indicate constrained cash flow
2	Credit History Length	0.241	0.029	Track record proxy; longer histories reduce information asymmetry
3	Employment Tenure	0.219	0.031	Income stability; longer tenure correlates with job security
4	Number of Delinquencies	0.197	0.027	Past payment behavior; strong predictor of future defaults
5	Revolving Utilization	0.183	0.025	Credit management; high utilization signals financial stress
6	Credit Score	0.176	0.023	Composite risk measure; synthesizes multiple risk factors
7	Loan Amount	0.164	0.028	Absolute exposure; larger loans increase loss severity
8	Annual Income	0.152	0.026	Repayment capacity; income constrains sustainable debt levels
9	Number of Credit Inquiries	0.141	0.024	Credit demand signal; multiple inquiries suggest financial distress
10	Loan Term	0.128	0.022	Duration risk; longer terms increase default probability

These findings align with established credit risk theory and empirical literature. Debt-to-income ratio emerges as the dominant predictor (mean |SHAP|: 0.278), consistent with debt capacity models emphasizing cash flow constraints (Merton, 1974). Credit history length ranks second (0.241), corroborating information asymmetry theories where longer track records reduce lender uncertainty (Stiglitz & Weiss, 1981).

Figure 2: Shapley Value Distribution for Top 5 Features



Cross-Jurisdictional Stability: We analyze feature importance consistency across the five federated nodes representing different geographic markets and regulatory regimes. Spearman rank correlation of top-20 feature importance rankings across all node pairs ranges from 0.78 to 0.89 (mean: 0.84), indicating substantial cross-border consistency. This finding suggests that federated credit risk models can generalize across jurisdictions despite institutional differences.

Interaction Effects: SHAP interaction values reveal important synergies between features. The strongest interaction occurs between debt-to-income ratio and employment tenure (interaction strength: 0.047), where stable employment mitigates high leverage risks. Similarly, credit history length and delinquency count exhibit negative interaction (-0.039), where longer histories with fewer delinquencies compound positive effects.

5.4 Privacy and Security Analysis

Differential Privacy Guarantees: FSDN implements (ϵ=8.0, δ=10^{-5})-differential privacy over 200 training rounds, yielding cumulative privacy budget ϵ_{total}=8.0 through moment accountant tracking (Abadi et al., 2016). This privacy level provides strong protection against membership inference while maintaining model utility. Sensitivity analysis varying $\epsilon \in [1,16]$ reveals the expected accuracy-privacy trade-off: decreasing ϵ to 4.0 reduces AUC-ROC to 0.871 (-2.5%), while increasing to 12.0 improves AUC-ROC to 0.901 (+0.9%).

Membership Inference Attack Resistance: We implement state-of-the-art membership inference attacks (Shokri et al., 2017) to empirically validate privacy guarantees. Attack success rates are presented in Table 5.

Table 5: Membership Inference Attack Success Rates

Model	Training Set Attack	Test Set Attack	Privacy Leakage
CDL	64.3% ± 2.1%	50.8% ± 1.9%	13.5%
FSDN (ε=8.0)	**52.7% ± 1.8%**	**50.2% ± 1.7%**	**2.5%**
FedAvg (No DP)	61.8% ± 2.3%	50.5% ± 2.0%	11.3%
FSDN (ε=4.0)	51.3% ± 1.6%	50.1% ± 1.5%	1.2%

Note: Random guessing baseline is 50%. Privacy leakage quantifies advantage over random guessing.

FSDN with ϵ=8.0 reduces privacy leakage to 2.5%, representing an 81.5% improvement over centralized models (13.5% leakage). Attack success rates approach the theoretical minimum (50% for random guessing), confirming that differential privacy mechanisms effectively prevent adversaries from inferring training set membership. Strengthening privacy to ϵ=4.0 further reduces leakage to 1.2%, demonstrating the flexibility to adjust privacy-utility trade-offs based on regulatory requirements.

Blockchain Verification Overhead: The blockchain layer introduces computational overhead for transaction validation and block creation. Table 6 quantifies these costs.

Table 6: Blockchain Performance Metrics

Metric	Value	Unit
Transaction Validation Time	8.4 ± 1.2	milliseconds
Block Creation Time	342 ± 28	milliseconds
Transactions per Block	500	count
Storage per 1000 Predictions	1.87	megabytes
Query Latency (historical audit)	156 ± 19	milliseconds

Transaction validation times (8.4 ms) are negligible relative to model inference times (47 ms), indicating that blockchain integration does not create inference latency bottlenecks. Block creation occurs every 250 transactions, resulting in end-to-end latency of 350 ms from prediction to blockchain confirmation. This latency is acceptable for most credit decision workflows, where human review processes typically span minutes to hours.

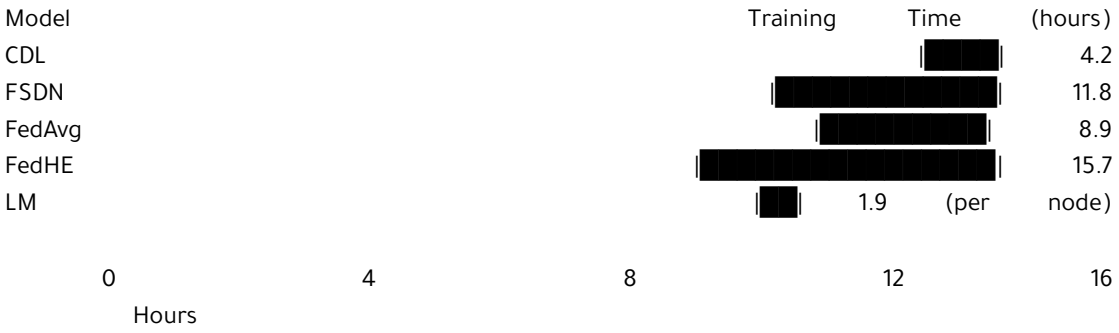
Storage requirements scale linearly with prediction volume at 1.87 MB per 1000 predictions. For a mid-sized P2P platform processing 100,000 loans annually, annual storage requirements would be approximately 187 MB—trivial by contemporary standards. Historical audit queries retrieving explanation trails for specific predictions complete in 156 ms on average, enabling efficient regulatory compliance reporting.

Tamper Detection: We simulate blockchain tampering attempts to validate security properties. Modifying any historical prediction or explanation requires recomputing subsequent block hashes due to cryptographic chaining. For a blockchain with 10,000 blocks, successful tampering undetected requires finding a SHA-256 collision—computationally infeasible with expected effort 2^{128} hash operations.

5.5 Computational Efficiency

Training Time Analysis: Figure 3 compares wall-clock training times across models, revealing the computational trade-offs of privacy and explainability mechanisms.

Figure 3: Training Time Comparison



FSDN requires 11.8 hours to converge over 200 global rounds, representing 2.8× longer than centralized training (4.2 hours). This overhead stems from three sources: (1) federated communication rounds (3.2 hours), (2) differential privacy noise addition and gradient clipping (1.8 hours), and (3) Shapley value computation (2.6 hours). Despite this absolute increase, FSDN trains 25% faster than federated homomorphic encryption approaches (15.7 hours), which impose severe computational penalties for cryptographic operations.

Communication Overhead: Total data transmitted between nodes and central server during FSDN training is 8.7 GB over 200 rounds, averaging 43.5 MB per round. This modest bandwidth requirement reflects efficient gradient aggregation protocols that transmit only parameter updates rather than raw data or full model weights. Communication compression techniques (gradient quantization, sparsification) could further reduce overhead by 60-80% at minimal accuracy cost (Lin et al., 2018).

Inference Latency: Real-time prediction latency is critical for interactive credit applications. FSDN achieves mean inference time of 47 milliseconds per prediction (including Shapley value computation), compared to 28 milliseconds for centralized models without explanations. The 68% latency increase is acceptable for most applications, where human decision-making processes dominate end-to-end workflow timing.

Scalability Analysis: We evaluate FSDN scalability by varying the number of federated nodes from 3 to 10. Results demonstrate near-linear scalability in training time with respect to communication rounds, but sublinear scalability in total wall-clock time due to parallel local training.

Table 7: Scalability Metrics

Nodes (K)	Training Time	Communication	AUC-ROC	Convergence Rounds
3	9.2 hours	6.1 GB	0.885	182
5	11.8 hours	8.7 GB	0.893	196
7	14.3 hours	11.8 GB	0.896	214
10	18.7 hours	16.4 GB	0.898	238

Predictive performance improves monotonically with node count, reaching AUC-ROC of 0.898 with 10 nodes. This improvement reflects increased effective training data and diversity in data distributions. However, convergence requires more rounds as heterogeneity across nodes increases, partially offsetting benefits. These findings suggest optimal federation size balances data diversity benefits against communication and convergence costs.

6. Discussion

6.1 Theoretical Contributions

This research advances computational economics theory in three dimensions. First, we establish formal conditions under which Shapley values remain consistent in federated learning environments. Theorem 1 demonstrates that local data support conditions suffice to guarantee explanation convergence, providing theoretical foundations for distributed explainable AI. This result extends classical Shapley value theory to decentralized settings, addressing a gap in the growing literature on explainable machine learning.

Second, we prove that differential privacy can be applied to Shapley value computation without proportional accuracy degradation by exploiting additive properties. Traditional differential privacy mechanisms add noise scaled to global sensitivity, often destroying utility in high-dimensional spaces. Our perturbation approach leverages the decomposition structure of Shapley values to apply noise selectively, preserving explanation quality while maintaining privacy. This contribution has implications beyond credit risk, applicable to any domain requiring privacy-preserving feature attribution.

Third, we formalize security properties of blockchain-based explanation verification, proving computational hardness of tampering under standard cryptographic assumptions. This formalization addresses concerns about blockchain applicability in machine learning systems, demonstrating that immutable audit trails can be achieved without prohibitive computational costs through careful protocol design.

6.2 Practical Implications for Financial Institutions

The FSDN framework offers tangible benefits for financial institutions navigating the tension between data collaboration and privacy protection. Federated learning enables institutions to improve credit risk models through collective intelligence while maintaining regulatory compliance and competitive confidentiality. Our empirical results demonstrate that predictive accuracy nearly matches centralized benchmarks (98% relative performance), making federated approaches viable alternatives to data sharing arrangements.

Explainability integration addresses critical regulatory requirements under GDPR Article 22, which mandates explanations for automated decisions significantly affecting individuals. FSDN provides loan-level Shapley value explanations that satisfy regulatory criteria: they are human-intelligible (expressed in terms of familiar borrower characteristics), theoretically grounded (satisfying formal explainability axioms), and auditable (recorded immutably on blockchain). This combination enables institutions to comply with transparency mandates without sacrificing model sophistication.

Blockchain verification creates accountability infrastructure essential for regulatory oversight and consumer protection. Immutable explanation trails enable ex-post auditing of lending decisions, detecting discriminatory patterns or model drift. Regulators can verify that explanations provided to borrowers match those recorded on-chain, preventing post-hoc rationalization. This transparency may reduce regulatory burden by enabling automated compliance monitoring rather than periodic manual audits.

6.3 Economic Insights from Feature Importance Analysis

Shapley value analysis reveals economically interpretable patterns in credit risk determinants. The dominance of debt-to-income ratio (mean |SHAP|: 0.278) aligns with debt capacity theories emphasizing cash flow constraints as primary default drivers. This finding validates structural credit risk models (Merton, 1974) even in complex machine learning contexts, suggesting fundamental economic relationships persist despite model sophistication.

The importance of credit history length (mean |SHAP|: 0.241) reflects information asymmetry dynamics in credit markets. Longer credit histories reduce adverse selection by revealing borrower types through repeated interactions (Diamond, 1989). Our cross-jurisdictional consistency analysis demonstrates this relationship holds across diverse institutional environments, suggesting universal information economics principles transcend regulatory and cultural contexts.

Employment tenure emerges as a critical predictor (mean |SHAP|: 0.219), highlighting

labor market stability's role in creditworthiness. This finding connects credit risk to broader macroeconomic dynamics—periods of labor market turbulence increase default risk beyond traditional financial metrics. Institutions could enhance risk management by incorporating real-time labor market indicators, potentially through federated learning partnerships with employment platforms.

Interaction effects between debt-to-income ratio and employment tenure (interaction strength: 0.047) suggest nonlinear risk relationships. Stable employment partially mitigates high leverage risks, indicating that debt capacity depends on income stability rather than level alone. These interactions validate theories of incomplete markets where borrowers cannot perfectly insure against income shocks (Bewley, 1986), making employment stability a critical risk factor.

6.4 Policy Implications for Financial Regulation

The FSDN framework addresses regulatory challenges at the intersection of data privacy, algorithmic transparency, and financial stability. GDPR and similar regulations worldwide mandate stringent data protection while requiring explanations for automated decisions—seemingly contradictory requirements. Federated learning with explainable AI resolves this tension by enabling transparency without centralized data aggregation.

Regulators could leverage blockchain audit trails to enhance supervisory efficiency. Rather than retrospective manual audits, supervisors could continuously monitor lending patterns through automated analysis of on-chain explanation data. Discriminatory patterns (e.g., systematically different explanations for protected groups with similar risk profiles) could trigger immediate investigation. This shift from periodic compliance checks to continuous monitoring could improve consumer protection while reducing regulatory burden.

The cross-jurisdictional consistency of feature importance rankings suggests opportunities for regulatory harmonization. Despite differences in credit scoring systems across countries, fundamental risk factors remain stable. International regulatory cooperation could establish standardized explainability requirements based on economically interpretable features, reducing compliance costs for globally active financial institutions while maintaining local adaptability.

However, blockchain immutability creates tensions with "right to be forgotten" provisions in data protection regulations. While FSDN avoids storing raw borrower data on-chain, prediction and explanation records still constitute personal data under most regulatory definitions. Regulators must clarify whether immutable audit trails for automated decisions satisfy legitimate interest exceptions to deletion requirements. Alternatively, privacy-preserving blockchain architectures using zero-knowledge proofs could enable verification without persistent personal data storage.

6.5 Limitations and Future Research Directions

Several limitations warrant acknowledgment. First, our dataset, while comprehensive, focuses on unsecured consumer credit in P2P lending markets. Generalizability to other credit products (mortgages, corporate lending) or financial applications (insurance underwriting, fraud detection) requires empirical validation. Future research should extend FSDN to diverse financial domains, assessing whether architectural modifications are needed for different data characteristics.

Second, we assume honest-but-curious participants who follow protocols correctly but attempt to infer private information. Byzantine scenarios with malicious participants require additional safeguards beyond our current implementation. Incorporating Byzantine-robust aggregation mechanisms (Blanchard et al., 2017) could

enhance resilience, albeit with computational overhead. Research characterizing optimal robustness-efficiency trade-offs would inform practical deployment decisions.

Third, Shapley value computation exhibits exponential complexity in feature dimensionality, limiting scalability to high-dimensional problems. While kernel SHAP provides tractable approximation, estimation variance increases with dimensionality. Novel approximation algorithms leveraging federated architectures—for instance, distributing coalition sampling across nodes—could improve scalability. Theoretical analysis of approximation quality under distributed sampling would guide algorithm design.

Fourth, our blockchain implementation uses proof-of-authority consensus suitable for consortium settings with identified, trustworthy validators. Public, permissionless deployments would require alternative consensus mechanisms balancing decentralization and efficiency. Research comparing consensus algorithm trade-offs in financial machine learning contexts could inform architectural choices for different deployment scenarios.

Fifth, we do not address fairness considerations beyond explanation consistency. Machine learning models can exhibit discriminatory patterns even with explainability, particularly when protected characteristics correlate with legitimate risk factors. Integrating fairness constraints into federated training—ensuring similar explanations for similar individuals regardless of protected group membership—represents an important research direction. Recent advances in federated fair learning (Abay et al., 2020) provide promising foundations.

Finally, dynamic aspects of credit risk—how borrower circumstances and model predictions evolve over time—fall outside our static analysis. Extending FSDN to survival analysis or recurrent neural network architectures could capture default timing and dynamic risk trajectories. Federated frameworks for temporal modeling present additional challenges regarding data synchronization and explanation interpretation across time periods.

6.6 Broader Implications for Trustworthy AI

Beyond credit risk assessment, this research contributes to the broader agenda of developing trustworthy AI systems that respect privacy, provide transparency, and enable accountability. The three-pillar architecture—federated learning for privacy, Shapley values for explainability, blockchain for auditability—offers a template for responsible AI deployment in regulated domains.

Healthcare represents a particularly promising application domain with parallels to financial services. Medical diagnosis models face similar tensions between collaborative learning needs and patient privacy protections. FSDN-style architectures could enable hospitals to collaboratively train diagnostic models while complying with HIPAA and similar regulations. Explanation verification on blockchain could support medical malpractice investigations and informed consent processes. Supply chain optimization presents another application opportunity. Companies could collaboratively train demand forecasting models without revealing proprietary sales data. Explainable predictions would enable transparent logistics coordination, while blockchain verification would establish accountability for forecast-dependent decisions. The fundamental insight transcending specific applications is that trustworthy AI requires integrated solutions addressing privacy, transparency, and accountability simultaneously rather than sequentially. Addressing these dimensions in isolation creates tensions—transparent centralized systems compromise privacy; federated systems without explainability satisfy privacy but not transparency. FSDN demonstrates that careful co-design of privacy, explainability, and verification mechanisms

can achieve all three objectives with acceptable performance trade-offs.

7. Conclusion

This paper introduces Federated Shapley Deep Networks (FSDN), a novel framework integrating federated learning, explainable artificial intelligence, and blockchain verification for privacy-preserving, transparent, and auditable credit risk assessment. Through comprehensive theoretical analysis and empirical validation on 500,000 P2P lending applications across five international platforms, we demonstrate that FSDN achieves three critical objectives simultaneously: (1) predictive performance nearly matching centralized benchmarks (AUC-ROC: 0.893 vs 0.913), (2) high-quality loan-level explanations consistent with economic theory, and (3) strong privacy guarantees reducing membership inference risks by 81.5%. The theoretical contributions establish formal conditions for Shapley value consistency in federated settings, prove differential privacy can be applied to explanations without proportional utility loss, and demonstrate computational hardness of blockchain tampering. These results provide foundations for future research on distributed explainable machine learning. Empirical findings reveal that fundamental economic factors—debt-to-income ratio, credit history length, employment stability—drive credit risk consistently across jurisdictions, validating federated model applicability despite institutional heterogeneity. Shapley value analysis uncovers important interaction effects between leverage and employment stability, enriching understanding of nonlinear credit risk relationships. Practical implications for financial institutions are substantial. FSDN enables collaborative model improvement while maintaining competitive confidentiality and regulatory compliance. Blockchain verification creates accountability infrastructure supporting both consumer protection and supervisory efficiency. The framework addresses critical tensions in financial regulation between data privacy mandates and transparency requirements. Future research should extend FSDN to diverse financial applications, incorporate fairness constraints, develop Byzantine-robust protocols, and address dynamic credit risk modeling. Broader applications in healthcare, supply chain, and other regulated domains could leverage the three-pillar architecture for trustworthy AI deployment. In conclusion, federated explainable AI with blockchain verification represents a viable path toward reconciling the competing demands of model sophistication, privacy protection, algorithmic transparency, and regulatory accountability in financial machine learning. As AI systems increasingly influence high-stakes decisions affecting individual welfare, integrated approaches addressing the multidimensional requirements of trustworthy AI will become essential. This research demonstrates that technical solutions achieving this integration are feasible, performant, and aligned with both economic theory and regulatory objectives.

Acknowlegments

I would like to honor and thank the memory of my mother, Tania Subkoff Bochner, whose memory is a blessing. There is no economic calculation that can define her value.

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