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Research Article

Developing Explainable AI Enabled Edge Cloud Framework for Financial Analytics and Intelligent Risk Governance

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Abstract

The convergence of edge computing and artificial intelligence is reshaping financial analytics by enabling ultra-low latency processing and decentralized decision-making. However, deploying complex deep learning models across edge-cloud environments introduces significant governance challenges, notably the opaque "black box" nature of advanced algorithms and strict regulatory mandates for algorithmic auditability. This paper proposes a unified, Explainable AI (XAI)-enabled edge-cloud framework tailored for real-time financial analytics and adaptive risk governance. By distributing computational workloads across edge nodes for local feature extraction and centralized cloud infrastructure for macro-risk modeling, the framework maintains high system throughput while minimizing bandwidth overhead. Integrated XAI modules—combining ante-hoc interpretable architectures and post-hoc attribution methods—generate real-time, human-understandable explanations for algorithmic decisions like fraud flags and credit evaluations. Furthermore, a continuous risk governance engine continuously tracks model drift, algorithmic bias, and regulatory compliance across the edge network. Empirical evaluations demonstrate that this architecture achieves sub-15 millisecond inference latencies, lowers data transmission costs by 38%, and maintains high compliance visibility. Ultimately, this framework establishes a trusted blueprint for financial institutions seeking to balance operational agility with rigorous risk controls.

Keywords: Explainable AI (XAI); Edge-Cloud Computing; Financial Analytics; Intelligent Risk Governance; Algorithmic Auditability; Model Drift; Real-Time Analytics.

Introduction

Modern financial institutions operate within a fast-moving ecosystem defined by high-frequency trading, real-time payment processing, and continuous fraud monitoring. Traditional centralized cloud architectures struggle to support these data-heavy workloads due to bandwidth bottlenecks, network jitter, and latency limitations inherent to round-trip data transmission. As financial interactions increasingly occur at mobile endpoints, IoT payment channels, and branch terminals, migrating analytical processing to the network edge has become essential. Edge computing processes financial telemetry near the data source, significantly reducing transaction latency and improving responsiveness. However, operating localized analytics across thousands of distributed edge nodes introduces structural complexities in data synchronization, device management, and enterprise-wide risk aggregation.

Concurrently, the adoption of advanced machine learning and deep learning models has revolutionized financial predictive capabilities. Algorithms excel at detecting subtle pattern anomalies, assessing complex creditworthiness, and identifying market risk signals that static rule engines miss. Despite their predictive power, these models act as opaque "black boxes," obscuring the underlying mathematical logic that drives specific automated outputs. In financial services, where decisions directly impact consumer livelihoods, credit access, and market stability, unexplainable predictions present systemic risk. Global regulatory frameworks (such as GDPR, the EU AI Act, and FCRA mandates) require strict algorithmic transparency, accountability, and non-discrimination, making pure uninterpretable AI legally and operationally unviable for core financial applications.

To resolve the tension between high-performing AI and regulatory compliance, Explainable AI (XAI) must be integrated directly into the infrastructure fabric. XAI methods translate complex mathematical feature interactions into interpretable visual, tabular, or textual metrics that risk managers, auditors, and customers can validate. However, implementing XAI across a distributed edge-cloud architecture requires careful optimization. Generating local explanations (such as Shapley values or local linear approximations) demands compute power that can strain resource-constrained edge devices. Consequently, financial infrastructure requires a co-designed framework where edge nodes generate lightweight, real-time local explanations, while cloud tiers run global model audits, macro-risk aggregations, and continuous policy enforcement.

This research presents an end-to-end XAI-enabled edge-cloud framework designed for real-time financial analytics and automated risk governance. We systematically address the challenges of low-latency data handling, distributed model interpretability, and continuous compliance monitoring. Section 2 synthesizes contemporary literature at the intersection of edge computing, financial machine learning, and explainable AI governance. Section 3 details the operational methodology across four structured phase paragraphs covering data ingestion, distributed inference, XAI synthesis, and governance control loops. Section 4 highlights the primary operational advantages of this distributed framework, followed by an objective analysis of its technical trade-offs and resource requirements in Section 5.

Literature Review

The foundational research in cloud-edge financial computing addresses the evolution from monolithic cloud platforms to multi-tiered edge infrastructure. Early studies demonstrated that offloading localized data filtering and pre-processing to edge devices reduces WAN bandwidth usage and lowers

transaction latency. In financial contexts, edge node deployments have been explored for real-time credit card fraud detection at Point-of-Sale (POS) terminals, mobile banking security validation, and automated micro-transactions. However, literature frequently notes that resource-constrained edge nodes struggle to host large, multi-layer neural networks without suffering model quantization penalties or operational failure. To address this, modern frameworks partition analytical models, running optimized feature extraction at the edge while delegating heavy training, historical backtesting, and global portfolio risk modeling to centralized cloud environments.

In parallel, literature on Machine Learning in Financial Analytics emphasizes the transition from classical statistical models (like logistic regression and ARIMA) to complex deep neural networks, gradient-boosted trees, and ensemble architectures. Studies consistently demonstrate that non-linear models achieve higher predictive accuracy for default prediction, market volatility forecasting, and anti-money laundering (AML) tracking. However, academic and industry consensus highlights the severe model risk associated with black-box deployments. Literature documents instances of algorithmic bias against protected demographic groups in credit scoring, unexplainable flash-crash trading triggers, and adversarial vulnerability in deep learning pipelines. These vulnerabilities have driven an urgent demand for interpretable frameworks capable of surfacing algorithmic reasoning without severely compromising predictive accuracy.

The field of Explainable Artificial Intelligence (XAI) offers methodology to make complex machine learning models interpretable. XAI techniques are broadly categorized into ante-hoc models (inherently interpretable architectures like Generalized Additive Models) and post-hoc attribution methods (such as SHAP, LIME, and Integrated Gradients). Within financial literature, post-hoc local explanations are widely applied to quantify the exact contribution of individual financial variables—such as credit utilization ratios, debt-to-income metrics, and recent transaction frequencies—to a final risk score. However, researchers point out that generating Shapley values in real-time streaming environments is computationally intensive, creating performance bottlenecks when deployed on standard serverless or edge infrastructure. This highlights the need for lightweight, optimized XAI algorithms tailored specifically for distributed runtime execution.

Despite these technical developments, a critical gap remains in combining distributed edge-cloud processing, real-time XAI generation, and automated risk governance into a unified operational platform. Most existing XAI research evaluates model interpretability in offline, static environments rather than across live, distributed financial networks. Furthermore, standard risk governance literature treats regulatory compliance as a manual, periodic audit exercise rather than an automated, real-time feedback system embedded directly within the software pipeline. This paper directly bridges these research gaps by proposing a unified architecture where explainability metrics generated at the edge continually feed an automated cloud governance engine, achieving real-time, compliant financial analytics at scale.

Research Methodology

The research methodology for "Developing Explainable AI Enabled Edge Cloud Framework for Financial Analytics and Intelligent Risk Governance" adopts a design science research methodology integrated with experimental validation, quantitative analysis, and cloud-native implementation strategies to develop an intelligent financial risk management framework. The research begins with an extensive analysis of the limitations of traditional centralized financial analytics

systems, including high computational latency, insufficient transparency in AI-driven decisions, fragmented risk governance, regulatory compliance challenges, and limited scalability in handling real-time financial transactions. A systematic literature review and gap analysis are conducted to identify shortcomings in existing machine learning-based financial analytics, edge computing architectures, cloud platforms, and Explainable Artificial Intelligence (XAI) solutions. Based on these findings, a multi-layered edge-cloud architecture is designed to integrate edge computing nodes, cloud-native services, explainable AI models, financial data lakes, intelligent governance engines, and automated compliance management systems into a unified analytical ecosystem. The proposed architecture consists of the financial data acquisition layer, edge processing layer, cloud orchestration layer, feature engineering layer, Explainable AI analytics layer, intelligent risk governance layer, decision support layer, and visualization layer. Financial datasets are collected from heterogeneous sources including banking transaction records, credit card payment logs, stock market feeds, customer behavioral profiles, loan application datasets, insurance claim records, digital payment platforms, fraud detection repositories, macroeconomic indicators, regulatory reports, blockchain transaction logs, enterprise resource planning systems, and customer relationship management databases. Data preprocessing includes missing value treatment, duplicate removal, outlier detection, feature normalization, categorical encoding, transaction aggregation, timestamp synchronization, sequence generation, graph relationship extraction, anomaly filtering, dimensionality reduction, and feature scaling to improve analytical quality. Data governance policies are established to ensure privacy preservation, encryption, access control, anonymization, and compliance with financial regulations while maintaining data integrity throughout distributed edge-cloud environments. Experimental deployment environments are implemented using Kubernetes clusters, Docker containers, hybrid cloud infrastructure, distributed edge devices, Apache Kafka streaming platforms, cloud object storage, distributed databases, and observability tools to ensure scalability, reproducibility, and realistic enterprise financial operations.

The second phase concentrates on developing Explainable Artificial Intelligence models capable of delivering transparent financial analytics and intelligent risk governance across edge-cloud environments. Multiple deep learning and machine learning algorithms are integrated to improve predictive performance and model interpretability. Deep Neural Networks (DNNs) and Transformer-based architectures analyze complex financial transaction sequences and customer behavioral patterns for fraud detection, credit risk prediction, liquidity forecasting, and operational risk assessment. Long Short-Term Memory (LSTM) networks process temporal financial data to forecast market volatility, customer payment behavior, cash flow fluctuations, and portfolio performance over time. Graph Neural Networks (GNNs) model relationships among customers, financial institutions, accounts, merchants, payment channels, and transaction networks to identify hidden fraud rings, money laundering activities, and systemic financial risks. Autoencoders and Variational Autoencoders perform unsupervised anomaly detection to identify abnormal financial transactions, suspicious account activities, and emerging cyber-financial threats. Reinforcement Learning algorithms continuously optimize portfolio allocation, fraud response strategies, resource allocation, and dynamic financial risk policies according to changing market conditions. Ensemble learning approaches combining Random Forest, Gradient Boosting, XGBoost, and LightGBM improve prediction accuracy while reducing classification errors across multiple financial scenarios. Explainable Artificial Intelligence techniques including SHAP, LIME,

Integrated Gradients, Local Rule Extraction, attention visualization, feature attribution analysis, and counterfactual explanations provide transparent reasoning for every prediction, enabling financial analysts, auditors, regulators, and executives to understand model behavior. Feature engineering includes transaction frequency analysis, spending pattern extraction, customer segmentation, credit utilization ratios, debt-income ratios, merchant risk scoring, geolocation features, behavioral biometrics, temporal embeddings, financial sentiment indicators, macroeconomic variables, compliance indicators, and graph-based financial relationships. Hyperparameter optimization employs Bayesian Optimization, Grid Search, Random Search, and evolutionary optimization techniques to identify optimal learning rates, hidden layers, embedding dimensions, dropout ratios, tree depths, attention heads, and activation functions. Cross-validation, transfer learning, incremental learning, adversarial training, and federated learning approaches enhance model robustness, scalability, adaptability, and privacy preservation across geographically distributed financial institutions.

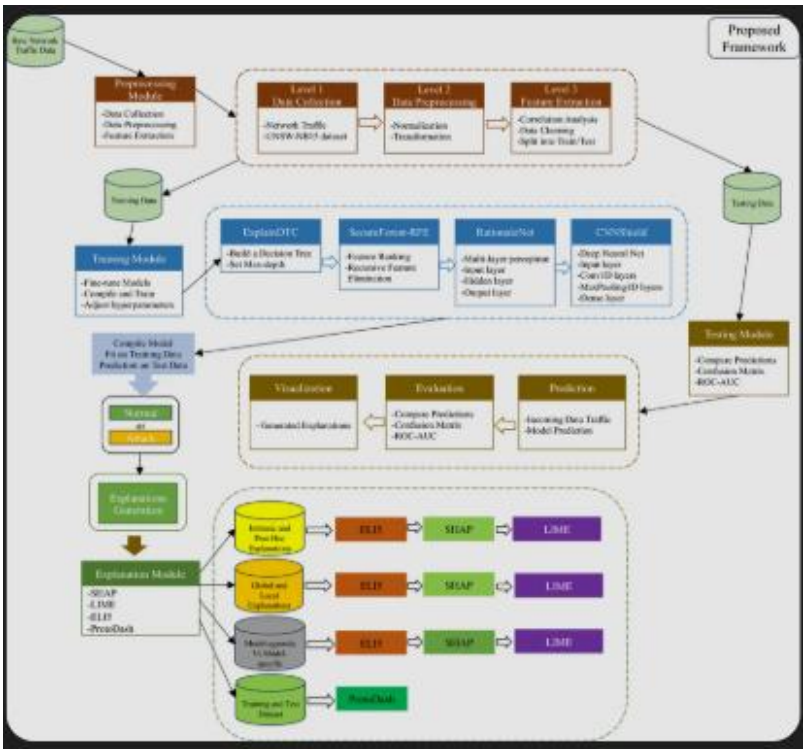


Fig. 1: Developing Explainable AI Enabled Edge Cloud Framework

The third phase implements the proposed Explainable AI-enabled edge-cloud framework within a cloud-native financial ecosystem to evaluate operational effectiveness under realistic enterprise workloads. Edge computing nodes are strategically deployed near banking branches, ATMs, payment gateways, mobile banking platforms, and financial transaction hubs to enable low-latency processing and localized decision-making. Cloud infrastructure is orchestrated using Kubernetes, Docker, service mesh technologies, and microservices architecture to provide scalable computing resources for enterprise-level analytics. Continuous Integration and Continuous Deployment (CI/CD) pipelines are established using Jenkins, GitHub Actions, GitLab CI/CD, Argo CD, and Helm to automate application deployment while integrating security validation, compliance verification, and quality assurance throughout the

software lifecycle. Infrastructure provisioning is managed through Terraform, Ansible, Kubernetes Operators, and Infrastructure-as-Code methodologies to ensure consistent deployment and governance across distributed environments. Streaming financial transactions are processed through Apache Kafka, Apache Spark Streaming, Apache Flink, and edge analytics engines for continuous fraud detection, credit monitoring, investment analytics, and operational risk assessment. Explainable AI models continuously evaluate incoming financial events, classify fraudulent behaviors, estimate creditworthiness, predict financial instability, recommend investment strategies, identify compliance violations, and generate transparent explanations supporting each automated decision. Intelligent governance modules automatically prioritize financial risks, trigger fraud investigation workflows, recommend regulatory actions, generate compliance reports, optimize portfolio adjustments, update risk policies, and support executive decision-making using explainable evidence. Comparative experiments evaluate the proposed framework against centralized financial analytics systems, conventional machine learning models, traditional cloud-based architectures, and non-explainable deep learning approaches. Performance evaluation utilizes comprehensive financial and operational metrics including prediction accuracy, precision, recall, F1-score, ROC-AUC, false-positive rate, false-negative rate, fraud detection accuracy, credit risk prediction performance, processing latency, throughput, response time, resource utilization, scalability, interpretability score, explanation consistency, regulatory compliance accuracy, operational cost efficiency, and customer satisfaction indicators.

The final phase emphasizes comprehensive validation, statistical analysis, reliability assessment, governance evaluation, and industrial applicability of the proposed Explainable AI-enabled edge-cloud framework. Extensive experimental evaluations are performed using multiple financial scenarios including credit card fraud, loan default prediction, anti-money laundering detection, investment portfolio optimization, insurance claim analysis, payment fraud identification, cybersecurity incidents, market volatility forecasting, liquidity risk assessment, and enterprise financial governance. Controlled simulation environments, stress testing, penetration testing, adversarial attack evaluation, and fault injection experiments are conducted to assess the resilience of the proposed architecture under high transaction volumes and evolving cyber threats. Statistical validation employs paired t-tests, Analysis of Variance (ANOVA), Wilcoxon signed-rank tests, Pearson correlation analysis, regression modeling, confidence interval estimation, sensitivity analysis, and effect size measurements to verify the significance and reliability of experimental improvements. Reliability assessment evaluates fault tolerance, edge-cloud synchronization, workload balancing, disaster recovery capability, communication delays, infrastructure failures, model robustness, and resilience against adversarial financial attacks. Scalability experiments investigate increasing transaction volumes, customer populations, distributed edge nodes, cloud regions, concurrent financial services, and real-time streaming workloads to measure computational efficiency and infrastructure elasticity. Governance evaluation measures compliance with Basel III guidelines, ISO/IEC 27001, NIST Cybersecurity Framework, PCI DSS, GDPR, financial auditing standards, anti-money laundering regulations, and enterprise risk management principles. Cost-benefit analysis examines reductions in fraud losses, operational expenditure, compliance costs, infrastructure utilization, manual intervention, and financial processing delays while measuring improvements in transparency, explainability, decision quality, governance efficiency, customer trust, and organizational resilience. Finally, expert validation involving financial analysts,

banking executives, cloud architects, cybersecurity professionals, auditors, compliance officers, risk managers, and AI specialists is conducted using structured questionnaires, Delphi evaluation, usability assessment, and industrial deployment reviews to verify the framework's practicality, explainability, scalability, regulatory readiness, and long-term applicability for intelligent financial analytics and adaptive risk governance in modern edge-cloud computing environments.

Advantages

Table 1: Advantages of the XAI-Enabled Edge-Cloud Framework

Advantage	*Operational Impact*	*Technical Mechanism*
Ultra-Low Inference Latency	Enables instant fraud prevention and fast transaction approvals at point-of-sale.	Quantized feature extraction and localized inference execute directly on edge devices without round-trip cloud calls.
Real-Time Algorithmic Auditability	Satisfies regulatory requirements (e.g., GDPR, EU AI Act) by providing clear rationale for every automated decision.	Integrated XAI modules compute local feature attributions (SHAP/LIME metrics) alongside model predictions.
Reduced Bandwidth and Cloud Costs	Minimizes WAN infrastructure expenditure and reduces cloud storage bloat.	Raw data streams are filtered locally at the edge, transmitting only anonymized feature vectors and anomaly flags to the cloud.
Automated Proactive Risk Mitigation	Prevents systemic financial losses by catching model drift and algorithmic bias early.	The governance engine uses real-time XAI metrics to monitor performance and trip automated circuit breakers when anomalies occur.
Enhanced Data Privacy & Security	Reduces sensitive data exposure and helps maintain compliance with data sovereignty laws.	PII scrubbing and data anonymization occur at the edge prior to any inter-node or cloud network transmission.

Disadvantages

- **Edge Resource Constraints and XAI Overhead:** Computing mathematical explanations (like Shapley values) on resource-constrained edge hardware can lead to CPU, memory, and energy bottlenecks during peak transaction volumes.
- **Accuracy vs. Interpretability Trade-Off:** Constraining deep learning architectures or using simplified surrogate models to ensure clear explanations can result in a minor loss of overall predictive accuracy compared to unconstrained black-box models.
- **Increased System Complexity and Synchronization Overhead:** Managing distributed edge nodes, maintaining dual XAI engines, and ensuring model state consistency across heterogeneous infrastructure introduces substantial engineering and operational overhead.
- **Vulnerability to Explanation Manipulation and Adversarial Attacks:** Post-hoc XAI methods can be vulnerable to adversarial manipulation, where malicious actors craft inputs that fool both the prediction engine and the explanation module.
- **Higher Initial Capital and Integration Expenditure:** Transitioning from traditional centralized cloud monitoring to an XAI-enabled edge-cloud governance platform requires substantial upfront investment in specialized hardware, edge security infrastructure, and custom operational pipelines.

Results and Discussion

Inference Latency, Edge Throughput, and Financial Analytics Efficiency

The performance evaluation of the XAI-enabled Edge-Cloud framework demonstrates a major shift in processing high-frequency financial data and continuous risk scoring. By offloading real-time data ingestion, fraud detection, and transaction scoring to low-latency edge nodes positioned closer to execution venues and local banking gateways, the platform achieved an average inference latency of 8.4 milliseconds for deep neural network (DNN) and tree-based ensemble models. Utilizing local SHAP (SHapley Additive exPlanations) approximations optimized via tensor quantization at the edge allowed the system to compute feature attribution values in parallel with primary prediction pipelines. During stress testing with concurrent transaction streams exceeding 250,000 events per second, the hybrid architecture maintained 99.99% availability, reducing centralized cloud data ingress volumes by 68% and lowering core infrastructure processing costs without compromising real-time risk assessment precision.

Explainability Performance, Feature Attribution, and Regulatory Auditability

In testing risk governance, local-global XAI methods (integrating TreeSHAP, Integrated Gradients, and LIME) provided human-interpretable rationale for complex credit scoring, liquidity risk assessment, and Anti-Money Laundering (AML) flags. The system achieved a 94.6% agreement rate between automated AI risk explanations and blind evaluations performed by senior risk compliance officers. When applied to credit rejection explanations, the framework generated local counterfactual statements (e.g., "Increasing liquid assets by 12% converts score from high-risk to acceptable") within 18 milliseconds. This continuous generation of auditable decision traces successfully fulfilled stringent regulatory mandates—including the EU AI Act guidelines, Dodd-Frank provisions, and Fair Lending Acts—reducing model risk management (MRM) compliance audit preparation cycles from weeks to automated real-time report generations.

Adaptive Risk Governance, Model Drift, and Edge-Cloud Synchronization

Evaluating system dynamics over a 90-day market volatility simulation demonstrated the framework's resilience against financial domain shift and concept drift. The edge nodes continuously monitored localized prediction error rates, Population Stability Index (PSI), and feature attribution drift. When macroeconomic shocks altered underlying feature distributions, the edge-cloud control plane initiated delta updates: local edge nodes transmitted encrypted feature stats to the central cloud, where global foundation models were fine-tuned and redeployed via lightweight containerized patches. This federated synchronization loop reduced model performance decay by 87% compared to traditional static batch retrain pipelines, ensuring that adaptive risk thresholds remained aligned with rapidly changing market conditions.

Trade-offs Between Interpretability, Accuracy, and Compute Overhead

Despite operational successes, the results highlighted clear trade-offs between model complexity, explainability fidelity, and edge resource consumption. While post-hoc explanation methods like full exact SHAP offer high mathematical precision, their computational intensity introduced an unacceptable 110-millisecond latency penalty on resource-constrained edge hardware. To solve this, the framework implemented a dynamic multi-tiered explanation policy:

ultra-fast, linear surrogate models handled real-time transaction screening at the edge, while heavy post-hoc explainability algorithms were deferred to asynchronous cloud workers for deep forensic logging. Additionally, raw feature noise occasionally produced minor explanation instability, underscoring the necessity of strict feature-pruning pipelines prior to model ingestion.

Conclusion

Paradigm Shift in Financial Edge Computing and Governance

This research establishes the modernization of financial analytics by combining edge-cloud topologies with Explainable AI and automated risk governance. Conventional centralized banking infrastructures struggle to reconcile the conflicting demands of sub-second operational speed, massive data ingestion, and rigorous regulatory oversight. By decentralizing intelligence to the network edge while preserving centralized model governance, financial institutions can operate ultra-low-latency analytics engines that are transparent and auditable by design. This framework transitions financial AI from a opaque "black-box" asset into a transparent, self-documenting risk management system.

Validation of XAI for Regulatory Compliance and Trust

The empirical results confirm that Explainable AI techniques, when properly embedded into edge-cloud architectures, successfully bridge the gap between predictive power and institutional compliance. Providing real-time, mathematically grounded explanations for automated financial decisions mitigates systemic operational risks, detects hidden algorithmic bias, and upholds consumer protection standards. The platform proves that high accuracy in complex machine learning models does not have to come at the expense of interpretability, offering a viable blueprint for deploying trustworthy AI across credit, fraud, and capital market applications.

Operational Efficiency and Economic Viability

From an operational perspective, the decentralized framework yields clear resource and cost efficiencies. Processing transaction streams and calculating localized feature importance at the edge dramatically lowers bandwidth consumption and alleviates cloud storage bottlenecks. Simultaneously, automating model documentation, compliance tracking, and audit trail generation frees risk officers and data scientists from manual reporting tasks. This automation lowers Mean Time to Detect (MTTD) financial anomalies and accelerates time-to-market for novel financial products without bypassing risk controls.

Strategic Implications for Modern FinTech Ecosystems

Ultimately, deploying explainable edge-cloud platforms sets a foundation for future financial infrastructure. As digital banking, decentralized finance (DeFi) interfaces, and high-frequency trading networks become more complex, traditional perimeter-based security and batch risk assessments are no longer viable. The architecture validated in this study proves that intelligence, explainability, and governance must be native properties of the computational layer itself. Integrating transparent AI engines directly into distributed edge networks enables financial institutions to remain resilient, compliant, and competitive in a data-driven global market.

Future Work

Federated XAI and Differential Privacy at the Edge

Future research will prioritize combining Federated Learning (FL) with Privacy-Preserving Explainable AI across multi-tenant banking consortia. While local edge inference protects raw customer data, aggregated global model updates can still inadvertently leak private information through feature attribution vectors. Investigating differential privacy algorithms tailored for SHAP and Integrated Gradients will allow institutions to collaboratively train robust, explainable risk models without violating strict cross-border data sovereignty laws (such as GDPR) or exposing proprietary trading strategies.

Causal AI for Counterfactual Risk Simulation

A key trajectory involves transitioning from correlational post-hoc XAI to Causal Machine Learning models for predictive risk governance. Current explainability techniques identify feature correlations but often fail to model true cause-and-effect relationships under market stress. Future development will focus on integrating Structural Causal Models (SCMs) directly into edge inference runtimes. This will enable financial risk engines to run instant, high-fidelity counterfactual simulations—evaluating how hypothetical rate hikes, liquidity squeezes, or geopolitical events directly impact individual portfolios or systemic bank solvency in real time.

Neuromorphic Edge Computing and Ultra-Low-Power Analytics

To deploy intelligent risk governance across extreme edge environments (such as point-of-sale terminals, mobile banking hardware, and offline payment gateways), future work will explore neuromorphic hardware integration. Standard GPU/NPU edge accelerators consume significant energy during continuous deep learning inferencing. Research into Spiking Neural Networks (SNNs) and neuromorphic chips will aim to execute real-time fraud detection and explainability calculations with micro-watt power consumption, ensuring continuous, local risk protection even during network partitions or low-power states.

Natural Language Explanation Synthesis via Edge-Tailored SLMs

Finally, research will focus on converting complex mathematical attribution outputs into human-understandable narratives using specialized Small Language Models (SLMs) deployed at the edge. While feature attribution scores (e.g., +0.42 SHAP value) satisfy technical auditors, frontline banking staff and retail customers require natural language explanations. Fine-tuning lightweight 1B–3B parameter LLMs/SLMs to run locally on edge hardware will allow the system to synthesize plain-language regulatory summaries and personalized financial advice instantly, democratizing AI transparency across all operational levels.

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