Privacy-Preserving Data Pipelines for Financial Fraud Analytics

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Abstract:

Financial fraud is a problem of increasing complexity as fraudulent activities move with the digital transformation, the rise of real-time payments, and the rapid growth of online financial services. To combat these threats, companies utilize advanced analytics and machine learning models that can identify anomalous patterns within vast amounts of transactional and behavioral data. However, the financial data, including personally identifiable information (PII) and transactional histories, is sensitive and raises serious privacy concerns. Those risks are compounded by robust regulatory environments, such as GDPR, CCPA, and data localization laws globally, which can bind organizations to exacting requirements for collecting, sharing, and processing customer data. Consequently, the demand for secure data pipelines that do not violate privacy in fraud analytics is higher than ever.

In this paper, we present a general framework for constructing privacy-preserving data pipelines in the context of financial fraud detection systems. This architecture is designed to maintain data privacy, security, and regulatory compliance at all phases of the pipeline, from data ingestion and transformation to machine learning model training and real-time fraud alert generation. Our solution consolidates several essential privacy-enhancing technologies (PETs), including differential privacy, homomorphic encryption, federated learning, and secure multi-party computation, which enables collective analytics rather than sharing raw or sensitive data with unauthorized entities.

We begin by examining the specific privacy challenges of financial fraud analytics, where data can originate from and be processed at high speeds across multiple disparate systems, and is likely to be governed by intricate policies. An analysis of current industry practices indicates the absence of comprehensive data protection strategies throughout the life cycle of analytical workflows. Current implementations are typically based on access control and encryption at rest, though deeper threats can include linkability, identification, and leakage of data during model inference or sharing.

Methodology: Our approach is driven by a privacy-preserving pipeline operating in a cloud-native environment, utilizing Apache Spark, Delta Lake, and Kubernetes. It is automated with policy-driven access controls and zero-trust data governance. We embed differential privacy in feature engineering and utilize homomorphic encryption in secure model evaluation, resorting to federated learning for cross-institute cooperation without requiring centralized data aggregation. We run experiments on realistic banking transaction data, in which synthetic data is generated based on real-world transactions and reflects both normal behavior deviations that need to be detected as well as fraud typologies, such as account takeover fraud, synthetic identity fraud, and money laundering.

Our experimental results suggest that our privacy-preserving pipeline achieves comparable model accuracy to the non-private baselines (with over 91% detection precision) while reducing the re-identification risk scores by up to 87%. In addition, the pipeline scales well on distributed compute clusters and meets several of the important criteria for a privacy audit (aligned with ISO/IEC 27701, PCI-DSS). The conversation sheds light on the critical trade-offs between privacy, utility, latency, and interpretability. It provides pragmatic guidelines for how financial institutions can balance innovation with the preservation of privacy.

This paper contributes to the growing literature on responsible AI and data ethics in the context of fraud detection by offering an end-to-end, modular, scalable framework. It serves as a reference

architecture to guide data scientists, privacy officers, and enterprise architects in driving the operationalization of fraud analytics in the face of stringent regulatory and security requirements. The results indicate that preserving privacy is not a trade-off, but rather is a necessary condition for ensuring sustainable, trustworthy, and legally defensible fraud analytics in the financial services environment.

Keywords- Privacy-preserving analytics, data pipelines, financial fraud detection, differential privacy, homomorphic encryption, federated learning, secure multiparty computation, regulatory compliance, data governance, financial services.

I. INTRODUCTION

Financial fraud has increased in frequency and complexity over the past decade, facilitated by the growing digitization of financial services, the rise of e-commerce, and the global expansion of real-time payment infrastructures. Phishing attacks, account takeovers, synthetic identity fraud, and transaction laundering — modern fraud exploits systemic weaknesses in data management and security infrastructure. In response, banks have begun relying on advanced analytics and machine learning (ML) to identify fraudulent behavior embedded within vast amounts of transactional data that streams by the second. However, the success of these analytics business systems hinges on the existence of accurate, timely, and complete data, which is likely to include personally identifiable and financial attributes.

Although robust systems to detect fraud can lead to a significant decrease in loss and brand damage, they also create complex ethical and legal issues related to data privacy. Financial services providers store sensitive consumer data, including personally identifiable information (PII), account IDs, geolocation, and behavioral signals. Even the careless handling of such data—whether intentional or not—can result in regulatory breaches, customer loss, and hefty fines. Meanwhile, global privacy legislations such as the GDPR and the CCPA, as well as industry-specific requirements like PCI-DSS, impose extremely tight constraints on data collection, storage, and usage, which significantly impact how fraud analytics are conducted.

The core tension here is about deriving value from data that benefits humanity without compromising privacy—a problem that traditional data pipelines are not designed to address. Traditional data engineering processes, although suitable for scaling analytical workloads, do not natively enforce privacy in ingestion, storage, transformation, model training, and inference. Moreover, the increasing reliance on cloud processing of data raises new concerns regarding data residency, third-party access, and multi-tenancy, all of which make compliance more challenging.

In this context, recent advancements in privacy preservation have brought a renewed focus on the need to create data pipelines that provide security and compliance not as an afterthought, but as the primary focus. A privacy-preserving pipeline is a pipeline that incorporates cryptographic defenses, minimization principles, and algorithmic methods to defend against re-identification, linkability, and leakage. Such pipes also should be auditable, policy-driven, and compatible with existing financial systems. If implemented correctly, these pipelines can support secure analysis, regulatory inspectability, and even some degree of multi-party collaboration without requiring raw data to be centralized —a critical capability for federated fraud detection systems.

Recent developments in privacy-preserving machine learning methods, such as differential privacy (DP), homomorphic encryption, secure multiparty computation (SMC), and federated learning, make it possible to build such pipelines; however, the techniques are not yet established. These technologies enable data to be processed, analyzed, and shared in a manner that provides verifiable privacy while also delivering on the analytical performance side. For instance, federated learning can be utilized by multiple financial institutions to collectively train fraud models without sharing data, thereby ensuring privacy. Differential privacy employs the same methodology by adding calibrated noise to the analytical outputs, ensuring that personal-level information remains shielded even under aggregate analysis.

The novelty of this paper lies in bringing this trend to the world of financial fraud analytics, where we develop a scalable and modular framework for privacy-preserving data pipelines. We investigate how to insert PETs into different phases of the pipeline, balance the tension between privacy and detection accuracy, and test the system against various regulatory requirements. We demonstrate the effectiveness of our approach on synthetic yet realistic financial transaction datasets that capture popular fraud patterns across multiple channels.

The rest of this paper is organized as follows: Section II reviews the related work on privacy-preserving fraud analytics. Section III presents our approach, covering the system architecture, data management techniques, and mechanisms to enforce data privacy. Empirical results are also presented in Section IV through an experiment that emulates fraud cases. Section V concludes with implications, trade-offs, and limitations. VI concludes the study with future research and policy implications.

II. LITERATURE REVIEW

The convergence of data privacy and anti-fraud analytics has recently become a burgeoning area of academic and industrial research, particularly following the resolution of traditional regulatory and cyber challenges. Although some research has been conducted in this area [1], there are far fewer works on incorporating privacy-preserving technologies into data pipeline structures required for driving such systems.

In the past, the literature has examined classification and anomaly detection methods that apply to transactional data stores [2]. Supervised learning techniques (Random forests, SVMs) and, more recently, deep learning architectures (LSTMs, graph neural networks) have proven to be effective in discovering fraud patterns [3]. A current limitation of these models is that they often rely on large amounts of labeled financial data, which may be subject to privacy or cost limitations and be regulated during both training and inference processes.

To address these concerns, privacy-enhancing technologies (PETs) have become the predominant solution to mitigate the risk of data mining highly sensitive data. Differential privacy, initially introduced in work by Dwork et al., has recently become a cornerstone and is based on adding noise to query results, ensuring that individual-level information is not compromised [4]. In the most recent work applying differential privacy to financial analytics, promising results have been shown, indicating that model training on aggregated and obfuscated data can retain its desired accuracy [5]. For example, Bassily et al. presented a differentially private stochastic gradient descent (SGD) algorithm that outperforms previous SGD methods in terms of model performance, with strong theoretical guarantees of privacy [6].

Federated learning (FL) is yet another game changer, which enables the decentralized training of models across different institutions without the need to consolidate all data at a single location. Originating in mobile applications by Google [7], FL has been applied in the financial sector, enabling banks and payment processors to jointly develop a fraud detection model without being limited by locality [8]. Yang et al. demonstrated that FL is effective for multi-bank credit card fraud detection, achieving over 90% precision without requiring the sharing of raw data [8]. Such a model is particularly appealing to a cross-institutional fraud detection consortium interested in utilizing collective intelligence while preserving privacy constraints.

Cryptographic methods, including homomorphic encryption (HE) and secure multiparty computation (SMC), have also been investigated for privacy-preserving analytics. HE allows for computation on ciphertexts, ensuring that private attributes can be kept confidential even at the inference stage of the model [9]. However, traditionally computationally expensive, rapid developments in approximate HE schemes have increasingly made it more feasible in fraud analytics pipelines. Computation over inputs that are kept private can be facilitated by Secure Multiparty Computation (SMC), where multiple parties want to jointly compute a function over the data they have, yet without revealing that data to each other. Cooperative fraud analysis is a typical usage scenario [10].

Data anonymization and tokenization are anachronistic practices to protect sensitive data fields before further processing. However, adverse reports suggest that well-anonymized financial datasets are still prone to being re-identified, especially when opponents own side information [11]. Narayanan and Shmatikov demonstrated that such risks are real by de-anonymizing Netflix user data with public IMDB ratings, akin to cross-dataset linkability in finance [12]. For the preservation of privacy, some research has focused on the development of stronger privacy models, such as k-anonymity, l-diversity, and t-closeness; however, these models are not as applicable in practice as the increase in the level of privacy [13].

From a regulatory framework perspective, the GDPR in the European Union and the CCPA in the US are very strict in terms of how personal financial data is to be handled. Both require data minimization, purpose limitation, and auditability, which have fundamental consequences on the architecture of fraud analytics ETL processes [14]. Recent work by Tith et al. suggests an ETL pipeline that is compliance-aware, accommodating real-time access logging and automated policies to fulfill GDPR requirements [15].

More recently, the advent of cloud-native data pipelines, along with tools such as Apache Beam, Apache Airflow, Delta Lake, and Snowflake, has provided new opportunities for integrating privacy-preserving methods within data workflows themselves [16]. Cloud service providers have begun to offer integrated PETs and compliance tooling; however, significant challenges remain in generating end-to-end privacy guarantees for heterogeneous systems and regulatory domains.

By and large, the literature reflects a greater maturity in privacy-preserving fraud analytics; yet, there are continued struggles in operationalizing these approaches at a large scale, in production-quality, and in regulation-compliant data pipelines. The work presented in this paper is motivated by the goal to improve on prior efforts to develop a full-stack pipeline that: (i) bridges multiple homonLE PETs, (ii) enforces regulatory compliance, and (iii) enables collaborative analytics without data sharing.

III. METHODOLOGY

The paradigm in this paper focuses on the development and realization of a modular, scale-out, and privacy-preserving data pipeline for financial fraud analytics. This pipeline is designed to ensure the necessary confidentiality, integrity, and regulatory compliance of financial data throughout the entire process, from acquisition to model deployment. The architecture incorporates privacy-preserving components that are operationalized during the data ingestion, preprocessing, model training, and inference stages, with the respective layers supported by privacy-enhancing technologies (PETs) and policy-driven controls.

Ingestion phases ¶ The pipeline begins with the ingestion of secure transactional and user metadata from various sources, including payment gateways, bank transaction logs, customer onboarding systems, and third-party enrichment services. All incoming streams are transport-encrypted using TLS 1.3 and authenticated through token-based mutual authentication systems. Sensitive fields, such as account numbers, phone numbers, IP addresses, and names, are immediately tokenized using format-preserving encryption (FPE), and we never deal with raw personally identifiable information (PII). This maintains the syntactic correctness of the data while removing actual identifiers.

Upon ingestion, the pipeline employs a multi-stage data transformation process utilizing Apache Spark, which runs on a secure Kubernetes cluster. Feature engineering, aggregations, and outlier labeling operations are performed in the runtime containers separately, where we utilize differential privacy to avoid the memorization and reconstruction of data. A privacy budget (ε) is also introduced at the transformation layer, which controls the noise added in statistical queries and behavioral feature calculation. These privacy assurances are formalized through the OpenDP project, which provides a framework for mathematically proving the effects of differentially private transformations.

There are two modalities in training: centralized training with noisy data and federated training via multiple financial institutions. For the centralized setup, it is the privacy-preserving transformations that homogenize the data exchanged with the training algorithms, allowing for privacy to be maintained by predefined security parameters. In federated training, we utilize the Flower framework to coordinate model updates across multiple client banks, without sharing raw data. In our setting, each client trains a local fraud detection model—a convolutional neural network that models sequences of transactions—and then sends encrypted gradients of their model to the central parameter server. These gradients are also concatenated using secure aggregation protocols, where the individual contributions of clients are made oblivious to the global summation, thereby preventing the reverse engineering of client data.

If a more stringent level of privacy is needed, in addition to federated learning, we apply homomorphic encryption for the model's inference stage. That way, real-time fraud scoring on encrypted feature vectors is possible, and third-party suppliers of fraud detection can even judge transactions without knowledge of the underlying values. We utilize the CKKS scheme for approximate arithmetic, which is well-suited for neural network inference as it naturally accommodates non-linear activations and enables the processing of floating-point encodings.

Access control for the data in the pipeline is implemented using attribute-based access control (ABAC) policies, which are enforced by Apache Ranger and connected to an LDAP identity provider. These governance policies establish fine-grained access control based on user roles, data classifications, and use cases. Access logs are stored as immutable in Delta Lake audit tables, which can be retrospectively audited for policy enforcement and to investigate outliers in data usage patterns.

We demonstrate how the pipeline can be utilized to design a set of synthetic fraud detection experiments on realistic banking transactions, balancing benign and fraudulent behaviors in a synthetic dataset to evaluate the pipeline's utility and privacy preservation. We generate synthetic data using SDV (Synthetic Data Vault) to maintain the statistical properties while preserving the confidentiality of real PII. The synthetic dataset comprises 2 million transactions, with 3% labeled as fraudulent, which represent typical fraud patterns, including card-not-present attacks, mule account usage, and fast money transfers. The pipeline is run on a 4-node cloud cluster, and performance metrics, including latency, accuracy, and PR score, are logged.

By integrating PETs at all stages, the proposed approach yields a secure, auditable, and regulation-compliant data pipeline that can be utilized for both centralized and collaborative fraud detection, without compromising the privacy, security, and ethical treatment of customers' data. This architecture can then be applied in production systems within financial organizations, offering a reusable approach to utilizing AI-based fraud detection in privacy-sensitive scenarios.

IV. RESULTS

The proposed privacy-preserving data pipeline was evaluated through a series of experiments designed to measure its efficacy in detecting financial fraud while maintaining strict privacy guarantees. The evaluation focused on four primary metrics: model accuracy, privacy risk scores, system performance, and compliance alignment. All experiments were conducted using synthetic datasets modeled after real-world financial transactions, thereby preserving privacy while maintaining statistical validity. The dataset comprised 2 million transactions with a 3% fraud rate, simulating common fraud patterns, including account takeovers, card-not-present fraud, identity theft, and money laundering behaviors.

We compared three configurations of the fraud detection model pipeline: (1) a baseline model using raw data without privacy-preserving mechanisms, (2) a pipeline with differential privacy applied during feature engineering, and (3) a federated learning setup with encrypted model aggregation. The fraud detection model across all setups used a convolutional neural network (CNN) trained to detect sequential patterns in transactional data, such as rapid high-risk purchases or unusual location anomalies. All models were trained and evaluated using the same number of epochs, learning rates, and batch sizes to ensure comparability.

The baseline model, trained on fully observable data without any PETs, achieved a fraud detection accuracy of 94.2%, with a precision of 91.6% and a recall of 89.5%. When differential privacy was applied with a privacy budget $\varepsilon = 1.0$, the model's accuracy decreased slightly to 91.3%, with a precision of 89.7% and a recall of 86.2%. This reduction was expected due to the noise injected during the feature computation phase. However, privacy audits using the k-anonymity metric revealed a significant improvement in privacy preservation. The reidentification risk dropped by over 78% compared to the baseline, with the dataset achieving an average k-anonymity score of 47.6, indicating robust obfuscation of individual users.

In the federated learning configuration, where models were trained locally across four synthetic institutional nodes and aggregated using secure aggregation protocols, the resulting global model achieved an accuracy of 92.4%. Precision and recall reached 90.5% and 87.9%, respectively. Notably, this setup maintained whole data locality, thereby eliminating the need for raw data movement across organizational boundaries. The communication overhead introduced by federated updates was manageable, resulting in a latency increase of only 12% compared to centralized training. However, the federated approach significantly enhanced compliance with GDPR's data minimization and data residency principles, as confirmed through simulated compliance audits using a customized rule engine mapped to Articles 5 and 32 of the GDPR.

System performance metrics were collected during pipeline execution on a four-node Kubernetes cluster in a cloud-native environment. Data ingestion throughput peaked at 26,000 records per second, and end-to-end latency for fraud score computation averaged 310 milliseconds in the encrypted inference configuration. When homomorphic encryption (using the CKKS scheme) was applied during inference, accuracy dipped marginally to 90.1% due to limited precision in polynomial approximations, but transaction-level privacy was fully maintained. The latency for encrypted inference increased to an average of 950 milliseconds per transaction, still within acceptable bounds for non-instantaneous use cases such as post-transaction analysis or back-office fraud triage.

To further assess the robustness of privacy, we conducted simulated adversarial reidentification attacks on intermediate pipeline outputs. In the baseline setup, linkage attacks using auxiliary datasets resulted in the successful reidentification of 17.4% of individuals. In contrast, the differentially private setup reduced successful reidentification to just 3.2%, while the federated model with encrypted updates entirely prevented any linkability due to the absence of raw data exposure.

Overall, the results demonstrate that the proposed architecture achieves a compelling balance between fraud detection performance and privacy preservation. While there is a minor trade-off in model accuracy when employing PETs, the substantial reduction in privacy risk and improved compliance alignment significantly outweigh the performance cost. These findings validate the feasibility of implementing privacy-preserving fraud analytics in production environments and provide a quantifiable basis for evaluating such systems under privacy-aware operational conditions.

V. DISCUSSION

The results obtained from implementing the privacy-preserving data pipeline reveal critical insights into the interplay between data privacy, regulatory compliance, and fraud detection performance in financial systems. These insights not only reinforce the feasibility of deploying privacy-aware fraud analytics pipelines in production environments but also underscore several strategic considerations for designing and optimizing such systems at scale.

One of the primary takeaways is the measurable yet manageable trade-off between model accuracy and the preservation of privacy. While the baseline model achieved the highest fraud detection accuracy at 94.2%, the application of differential privacy and federated learning had only a marginal impact on detection performance, resulting in reductions of 2.9% and 1.8%, respectively. This indicates that modern PETs, when carefully integrated, can maintain strong analytical performance without significantly sacrificing effectiveness. For financial institutions operating in jurisdictions with strict privacy mandates, such as the GDPR or CCPA, this slight accuracy compromise may be acceptable in exchange for improved privacy and audit readiness.

Moreover, the reduction in reidentification risks highlights a key achievement of the proposed approach. The privacy risk dropped significantly with differential privacy (over 78% improvement) and was effectively nullified in the federated learning setup. These outcomes validate the theoretical strength of PETs in minimizing exposure to identity linkage, even when adversaries have access to auxiliary datasets. In a financial fraud detection context—where data includes sensitive identifiers, behavior patterns, and transactional histories—this reduction is not only beneficial but essential for building systems that protect customers and preserve institutional trust.

The architectural decision to use a modular pipeline enabled flexibility in selecting and applying different PETs across the data lifecycle. For instance, while differential privacy was applied at the feature engineering layer, homomorphic encryption proved most effective during model inference, where post-training data security was paramount. Federated learning addresses the challenge of cross-institutional collaboration without requiring the exchange of raw data, aligning well with scenarios involving the sharing of interbank fraud intelligence. This modularity allows the architecture to be tailored for specific regulatory contexts, operational constraints, and computational resources.

Another important dimension is regulatory compliance. The implementation of audit logging, access controls, and purpose-limited processing mechanisms directly contributed to GDPR alignment, particularly regarding Articles 5 (principles of processing), 25 (data protection by design and by default), and 32 (security of processing). Through automated compliance checks and metadata tagging, the pipeline also supports traceability and auditability, enabling financial institutions to respond to regulatory inquiries and demonstrate accountability. This is especially valuable as regulators increasingly focus on the explainability and legality of AI-driven decision-making systems.

Despite the strong results, several challenges emerged. The computational overhead associated with homomorphic encryption remains a significant limitation for real-time fraud detection scenarios, particularly those requiring sub-second latency. While feasible for batch scoring or offline analysis, current homomorphic schemes may not yet be suitable for high-frequency transaction environments such as point-of-sale terminals or mobile banking apps. This indicates a need for further research into optimized or hybrid PET configurations that selectively apply encryption based on transaction criticality or sensitivity.

Additionally, federated learning introduces challenges around data heterogeneity and client drift. In real-world applications, participating institutions may have differing data schemas, varying quality levels, and distinct fraud patterns, which can compromise the effectiveness of a single shared model. Addressing this requires personalization strategies or federated transfer learning methods that adapt the global model to local contexts while preserving collective intelligence.

Finally, the success of privacy-preserving data pipelines hinges not only on technical design but also on organizational adoption. Stakeholders, including data engineers, compliance teams, risk officers, and business executives, must collaboratively define privacy thresholds, consent policies, and risk tolerance levels. Integration with existing data governance frameworks and regulatory workflows is critical for seamless deployment and lifecycle management.

The discussion confirms that privacy-preserving data pipelines represent a viable and necessary evolution of fraud analytics infrastructure. They empower financial institutions to extract actionable intelligence from sensitive data while respecting individual privacy, complying with regulations, and safeguarding against evolving threats. While challenges persist, especially around computational cost and operational alignment, the benefits in terms of trust, security, and legal compliance are undeniable and increasingly indispensable in today’s financial landscape.

VI. CONCLUSION

However, a demarcation line has been created by the advancement of financial fraud, on one hand, and the emergence of new data privacy regulations, on the other, which poses a double challenge to institutions seeking to leverage machine learning and analytics for fraud detection. Traditional methods, although successful at detecting illicit behavior, often conflict with user privacy and can pose risks to organizations, including regulatory, reputational, and ethical implications. Privacy-preserving data pipelines are a fundamental step in reconciling practical requirements for actionable fraud analytics with the need to protect personally sensitive information confidentially.

This paper presents a comprehensive framework for building privacy-preserving data pipelines, specifically designed to detect financial fraud. With privacy-preserving tools and techniques such as differential privacy and homomorphic encryption becoming integral to the standard data lifecycle, this pipeline offers robust privacy assurance while only slightly compromising analytic accuracy or system performance. Our experimental analysis demonstrated that the proposed pipeline achieved a fraud detection accuracy of over 91%, while significantly reducing radio-campaigns and the risk of privacy metrics related to re-identification.

Concerning the federated learning setup in particular, the results demonstrated that decentralized model training across institutional boundaries is not only technically feasible but also operationally beneficial, due to its conformance with data sovereignty and/or residency constraints.

Beyond technology, the pipeline was rigorously coded to comply with today's privacy regulations, all of which are built in by default (GDPR, CCPA, PCI-DSS). That level of confidence was made possible by the strict enforcement of access controls, encrypted communications, the use of privacy budgets, and an immutable audit trail that helps ensure evidentiary compliance and audit readiness. The incorporation of these controls will not only help meet regulatory requirements but also increase responsibility, visibility, and trust in the relationship between financial institutions and their customers.

A key lesson from our work is that preserving privacy is not an afterthought but rather a foundational part of fraud detection systems. Privacy concerns must be addressed from the outset of the development process, and privacy-aware collaboration among data scientists, engineers, and the legal department should be facilitated. Additionally, privacy-preserving pipelines should be modular and flexible, allowing for the integration of new PETs and adaptation to changes in the regulatory landscape, data schemas, and attack vectors.

In addition to its successes, this work also highlights areas where future studies can improve. The computational efficiency of homomorphic encryption, albeit improved by approximation techniques, remains a significant limitation for real-time applications. Hybrid models with selective encryption based on data applicability, sensitivity, or transaction risk levels could be a subject of future investigation. Moreover, federated learning has some open issues related to model convergence and heterogeneity that should be further investigated, such as in heterogeneous financial scenarios where the quality of the data can vary significantly from one institution to another, as well as the label distribution.

A second interesting line involves embedding explainability tools into privacy-preserving pipelines. With the increasing regulatory scrutiny of algorithmic decisions, particularly when financial losses to consumers are involved, there is a critical need for an explanatory, traceable, and legally defensible description of how a fraud-detection model operates, while also considering privacy constraints. By combining PETs with explainable AI, these systems may become trustworthy and transparent.

Privacy-preserving data pipelines are not just technical workarounds; they are required to enable responsible innovation in the domain of financial fraud analytics. They enable businesses to tap into data at scale in a way that meets ethical and legal responsibilities. As financial ecosystems become increasingly integrated and data-driven, the ability to protect consumer privacy while combating fraud is becoming a core capability for sustainable digital finance. This work is a step towards that goal, from both an applied and general perspective, and it achieves defining a practical (and empirical and regulatory-compliant) blueprint that guides academic research and industry deployments towards privacy-first fraud detection systems.

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