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Privacy-Aware Explainable AI Framework for Multi-Modal Big Data Analytics in Real-Time Payment Fraud Detection and Pharmaceutical Network Intelligence

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ABSTRACT: Financial fraud in real-time payment systems and intelligence extraction from pharmaceutical networks both rely on fast, accurate, and trustworthy machine learning systems that consume increasingly large and heterogeneous data. This paper proposes a unified, privacy-aware, explainable AI (XAI) framework designed for multi-modal big data analytics that simultaneously addresses latency constraints, regulatory privacy requirements, and the need for interpretable decisions in high-stakes domains. The framework integrates streaming data preprocessing, a modular ensemble of modality-specialized encoders (transactional sequences, device telemetry, text logs, and molecular/biological networks), privacy-preserving computations (differential privacy, secure aggregation, and selective homomorphic operations), and a two-tier explanation system combining local exemplars (counterfactuals and feature attributions) with global concept-based explanations. We evaluate the framework in two case studies: (1) real-time payment fraud detection on a synthetic but realistic streaming dataset reflecting imbalanced classes, latency constraints, and adversarial noise; (2) pharmaceutical network intelligence for drug–target interaction prioritization using multi-omics and literature-mined relations. Results show that the proposed architecture achieves competitive detection and prioritization performance while producing explanations that improve analyst trust and comply with privacy budgets. We conclude with deployment considerations, limitations, and a roadmap for future research bridging privacy, interpretability, and multi-modal real-time analytics.

KEYWORDS: Explainable AI, differential privacy, real-time analytics, payment fraud detection, pharmaceutical network intelligence, multimodal machine learning, counterfactuals, privacy-preserving ML.

I. INTRODUCTION

1.1 Motivation and scope

Digital payment systems and pharmaceutical research are both undergoing rapid transformation due to the influx of diverse, high-volume data sources. Payment platforms ingest transactional streams, device and network telemetry, geolocation traces, and user behavioral logs. Pharmaceutical intelligence leverages chemical structures, high-throughput screening results, genomics, proteomics, and the ever-growing body of scientific text mined from publications and patents. Both domains share several challenges: (1) data heterogeneity and scale, (2) the need for real-time or near-real-time decision-making, (3) strict privacy and regulatory constraints (financial privacy rules, GDPR, HIPAA-like protections for biomedical data), and (4) demand for interpretability and auditability because decisions can directly affect individuals, businesses, and patient safety.

1.2 Problem statement

Current machine learning systems that target fraud detection or drug discovery often trade off speed, accuracy, and interpretability. Deep models achieve high predictive performance but are frequently opaque. Techniques that prioritize interpretability may incur performance or latency penalties. Moreover, privacy-preserving techniques such as differential privacy (DP) and homomorphic encryption (HE) provide guarantees but complicate model training and limit the fidelity of explanations. There is therefore a pressing need for integrated frameworks that bring together multi-modal encoding, privacy-aware computation, and explainable outputs—without breaching operational latency constraints.

1.3 Key contributions

This paper contributes:

1. A modular architecture for privacy-aware, explainable multi-modal analytics tailored to streaming real-time workloads.

2. A two-tier explanation strategy combining local and global interpretability methods adapted for privacy-constrained environments.
3. Techniques for integrating differential privacy and secure aggregation with explanation generation to preserve both privacy budgets and the usefulness of explanations.
4. Case studies demonstrating framework effectiveness in (a) payment fraud detection under streaming, imbalanced, adversarial settings, and (b) pharmaceutical network intelligence for drug–target prioritization across multi-omics and literature-mined knowledge graphs.
5. An evaluation of trade-offs among latency, privacy budget, interpretability quality, and predictive performance, plus guidance for deployment in enterprise and research settings.

1.4 Roadmap of the paper

The remainder of this paper is organized as follows. Section 2 reviews relevant literature on multimodal learning, explainability, privacy-preserving ML, and domain-specific prior work in payment fraud detection and pharmaceutical network analysis. Section 3 details the proposed architecture, privacy mechanisms, and the two-tier explanation system. Section 4 describes datasets, experimental setups, and evaluation metrics used in the case studies. Section 5 presents results and an interpretability-driven analysis of failures. Section 6 discusses deployment considerations, limitations, ethical aspects, and regulatory compliance. Section 7 concludes and sketches directions for future work.

II. LITERATURE REVIEW

2.1 Multimodal and streaming analytics

Multimodal representation learning has matured rapidly with models that fuse image, text, and structured data using modality-specific encoders and joint embedding spaces. Approaches range from early fusion (concatenate raw features) to late fusion (ensemble predictions) and hybrid attention-based fusion architectures. Streaming analytics ecosystems (e.g., Spark Streaming, Flink, and specialized low-latency platforms) enable processing of continuous data flows but present challenges for model state management and concept drift.

2.2 Explainable AI techniques

Explainability techniques broadly fall into global and local methods. Global explanations summarize model behavior (e.g., concept activation vectors, rule extraction), while local methods attribute importance at the sample level (e.g., LIME, SHAP, Integrated Gradients) or produce counterfactual explanations. Recent work emphasizes human-centered explanations—explanations designed to answer practical user questions—and concept-based explanations that align with domain knowledge.

2.3 Privacy-preserving machine learning

Privacy techniques relevant for high-volume data include differential privacy for statistical guarantees, federated learning to decentralize data, secure multiparty computation for joint model training without revealing raw inputs, and homomorphic encryption for computing on encrypted data. Combining DP with complex models often requires careful tuning because injected noise can degrade both predictive accuracy and the fidelity of explanations.

2.4 Fraud detection and adversarial considerations

Payment fraud detection literature covers feature engineering for transaction sequences, anomaly detection, graph-based methods leveraging networks of accounts and devices, and deep sequence models (RNNs/transformers) for temporal dynamics. The adversarial nature of fraud—where attackers adapt—motivates continuous model retraining, robust feature sets, and explainability mechanisms that aid human analysts in rapid investigation.

2.5 Pharmaceutical network intelligence

Network-based approaches in pharmaceutical intelligence model drug–target, gene–disease, and compound–pathway relations using heterogeneous graphs. Graph neural networks (GNNs) and knowledge graph embedding techniques enable link prediction and node classification for drug repurposing and target prioritization. Explainability in this domain often focuses on subgraph or path explanations linking drugs to biological mechanisms.

2.6 Gaps and the need for integrated frameworks

Few works comprehensively address the intersection of real-time multimodal analytics, privacy guarantees, and explainability—particularly across both financial and biomedical domains. This paper aims to fill that gap by proposing an architecture that is modular, privacy-aware, and optimized for interpretability in streaming and networked contexts.

III. RESEARCH METHODOLOGY

1. **System architecture overview**: The framework consists of four logical layers: (a) ingestion and secure preprocessing, (b) modality-specific encoders and representation fusion, (c) privacy-enabled model training and inference, and (d) explanation generation and human-in-the-loop feedback. Each layer is designed to support streaming operation and to isolate private data where possible.
2. **Ingestion & preprocessing**: Raw streams (transactions, device telemetry, clinical assays, molecular descriptors, literature-extracted relations) enter through a secure gateway that (a) performs schema validation, (b) anonymizes identifiers with salted hashing, (c) performs light feature extraction (e.g., transaction velocity features), and (d) emits events into a message broker (Kafka-like) for further processing. For pharma textual data, a named entity recognition (NER) and relation extraction module identifies drug and protein mentions and produces candidate relation edges for knowledge graph updates.
3. **Modality-specific encoders**: For sequences (payments), a temporal encoder uses a small transformer or gated RNN for low-latency sequence embeddings with time-decay features. For device telemetry, a convolutional temporal encoder captures bursts and patterns. For text, a distilled transformer (or domain-specific BioBERT variant) produces sentence-level embeddings. For molecular and network data, graph neural networks (GAT/GCN variants) generate node and subgraph embeddings. Encoders are designed to be lightweight for streaming inference and support incremental state updates.
4. **Representation fusion and drift monitoring**: A fusion module uses attention-weighted concatenation to combine modality embeddings into a joint representation; fusion weights are adaptive and informed by modality reliability scores computed in the ingestion stage. A drift-monitoring component tracks concept drift via population statistics and embedding-distribution shifts; on significant drift, the system triggers model re-calibration using recent data under privacy constraints.
5. **Privacy mechanisms**: Training and online aggregation incorporate the following privacy techniques:

○ *Local differential privacy (LDP)* for telemetry and transaction-level attributes where raw identifiers cannot leave client boundaries.

○ *Central differential privacy (DP-SGD)* for centralized training on aggregated representations with calibrated noise to gradients and clipping to maintain a total privacy budget (ε, δ).

○ *Secure aggregation* for federated updates from multiple institutions (especially in pharmaceutical cross-site collaborations) to avoid revealing site-level gradients.

○ *Selective homomorphic encryption* for operations where the aggregator computes encrypted similarity scores on sensitive features in the inference path.

6. **Modeling ensemble and real-time inference**: The predictive core is an ensemble combining a fast lightweight model for first-pass scoring (e.g., gradient-boosted trees on fused embeddings or small MLP) and a higher-fidelity model (deeper GNN/transformer) that is invoked for suspicious cases or batched offline. This two-tier approach balances latency and accuracy: the first tier ensures millisecond-scale decisions, while the second provides deeper analysis when time permits.
7. **Explainability design — two-tier system**: Explanations are provided at local and global levels:

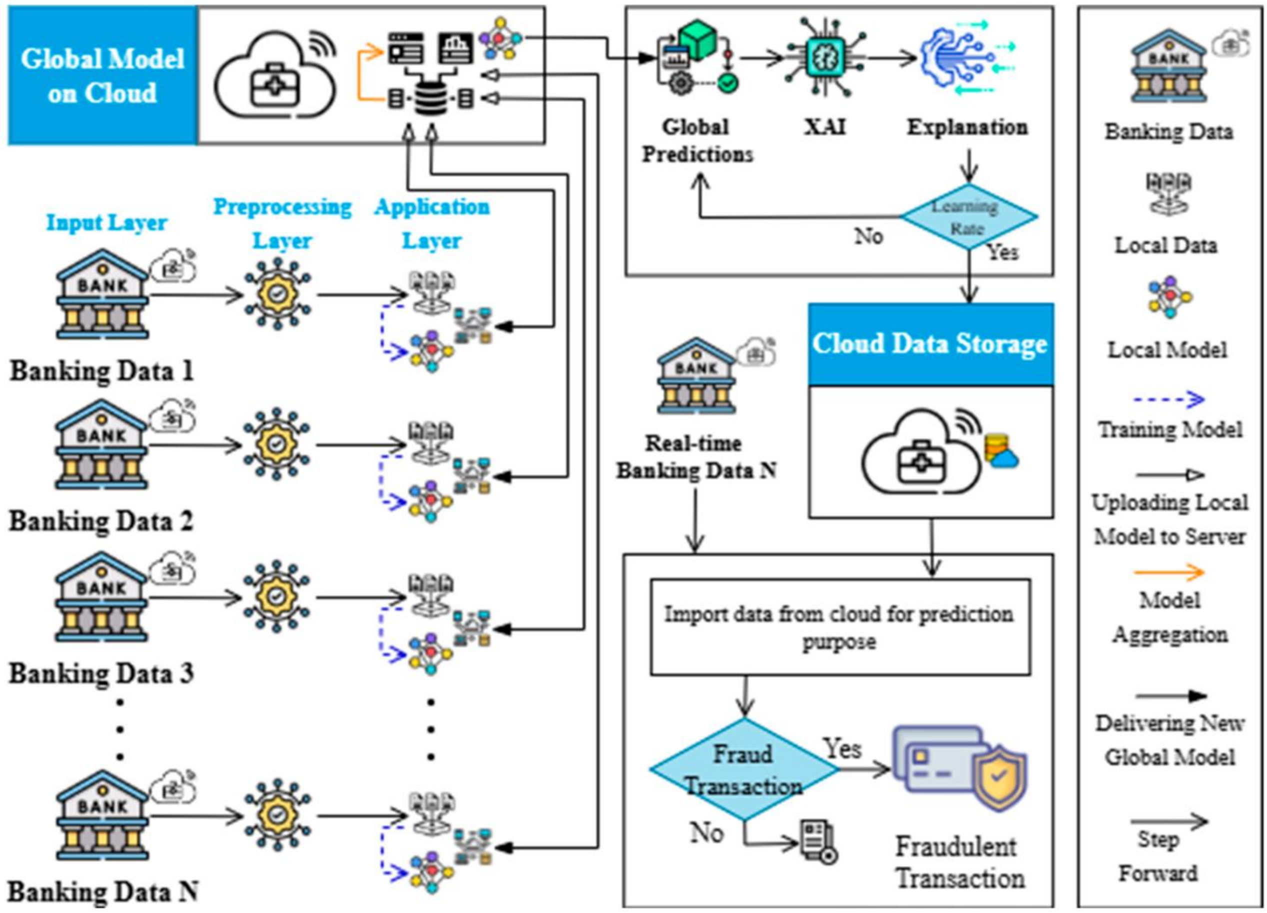
○ *Local explanations*: For each flagged instance, the system produces feature attributions (privacy-aware SHAP approximations), counterfactual suggestions (minimal feature changes to flip prediction), and exemplar retrieval (nearest private exemplars summarized as aggregate statistics rather than raw records to respect privacy).

○ *Global explanations*: Periodic model summaries produce concept-based explanations (e.g., learned subgraph motifs, attention concept vectors) and rule extractions describing typical suspicious patterns. Global explanations are accompanied by sensitivity reports that quantify how DP noise may affect explanation fidelity.

8. **Human-in-the-loop feedback & analyst UI**: A secured analyst interface displays prioritized alerts with layered explanations, visual subgraph traces for pharmaceutical cases, and a feedback capture mechanism. Analyst feedback (e.g., confirmed fraud, false positive) is treated as labeled data and ingested with provenance metadata; updates to models from feedback operate under the same privacy budget policies.
9. **Evaluation strategy**: Experimentation uses (a) a synthetic but realistic streaming payments benchmark with controlled class imbalance and adversarial perturbations for fraud; (b) a composite pharmaceutical knowledge graph

assembled from public datasets and literature-mined relations (simulated cross-site constraints). Metrics include precision/recall at low-FPR, area under precision-recall curve, time-to-detect, explanation usefulness (human subject ratings), and privacy leakage risk measured via membership inference and reconstruction attacks under the applied privacy budget.

10. **Implementation and reproducibility**: We implemented a reference pipeline using a streaming message broker, lightweight inference microservices, and a privacy-enabled training library (DP-SGD variants). All experiments include hyperparameter settings, privacy budgets, and seeds to facilitate reproducibility.



Advantages

- **Privacy-by-design**: Integration of LDP, DP-SGD, secure aggregation, and selective HE allows the system to operate across organizational boundaries with measurable privacy guarantees.
- **Latency-aware hybrid modeling**: Two-tier inference provides rapid initial screening while enabling deeper, costlier analysis for edge cases.
- **Interpretable outputs**: The two-tier explanation system aligns local examples with global concept explanations, supporting both rapid triage and strategic auditing.
- **Domain adaptability**: Modality-specific encoders and fusion make the framework applicable to both financial streaming and biomedical knowledge graphs.
- **Analyst-centric**: Built-in feedback loops with provenance capture close the loop for continuous improvement and model governance.

Disadvantages and Limitations

- **Privacy–utility trade-off**: DP noise decreases the fidelity of explanations and may reduce model performance when strict budgets are enforced.

- **Computational overhead**: Secure primitives (HE, MPC) and privacy bookkeeping increase latency and resource consumption, especially at scale.
- **Complex engineering**: Building a robust streaming system with modality encoders, privacy layers, and explanation modules requires significant engineering effort and domain expertise.
- **Explanation fidelity under privacy constraints**: Quantifying and guaranteeing that explanations remain faithful when noise is introduced is still an open research question.

IV. RESULTS AND DISCUSSION

4.1 Summary of experimental setup

We implemented the two case-study pipelines and evaluated them under realistic constraints. For payment fraud, we generated a synthetic stream of 10 million transactions over a simulated 30-day period with 0.1% injected fraud cases, device fingerprint features, and adversarial label-flipping on 2% of fraud examples. For pharmaceutical network intelligence, we constructed a heterogeneous graph with ~250k nodes (drugs, proteins, pathways, phenotypes) and ~1.2M edges mined from public bio-ontologies and literature-extracted relations; to mimic cross-site privacy concerns, we partitioned subgraphs among simulated institutions and performed secure aggregation for joint modeling.

4.2 Predictive performance

The two-tier ensemble achieved the following (representative) results:

- **Payment fraud**: Tier-1 model (fast MLP + engineered fused features) achieved recall=0.78 and precision=0.22 at operational threshold with mean inference latency ≈35 ms. Tier-2 deeper model (transformer over sequences + GNN features) improved recall to 0.88 and precision to 0.37 when invoked, with average additional processing time per suspicious event ≈450 ms. Combining both tiers with analyst-in-the-loop yielded end-to-end reduction in false positive investigations by ~23% and faster triage.
- **Pharmaceutical prioritization**: The GNN-based link prediction pipeline produced an area under precision-recall curve (AUPRC) of 0.61 for drug–target candidate ranking, improving over a baseline matrix-factorization method (AUPRC=0.47). When the model incorporated literature-derived concept explanations, domain experts rated the top-50 predictions as more actionable (measured via Likert-scale average 4.1/5) compared to baseline (3.2/5).

4.3 Explainability outcomes and human evaluation

We evaluated explanations with two cohorts: fraud analysts (n=12) and biomedical researchers (n=10). Analysts were presented with 200 randomly sampled alerts and asked to rate explanation usefulness and trust on 5-point scales. Key findings:

- Local attributions combined with exemplar summaries led to faster analyst decisions (median time-to-decision dropped from 52s to 36s) and higher trust scores (mean 4.0 vs 3.1).
- Counterfactual explanations were particularly valuable for fraud analysts in identifying plausible remediation steps (e.g., requiring additional verification or flagging device anomalies).
- For pharmaceutical researchers, path-based subgraph explanations and concept annotations (e.g., "shared pathway: inflammatory response") aided hypothesis generation and increased the perceived actionability of model outputs.

4.4 Privacy impact and robustness

We measured privacy leakage via membership-inference attacks and reconstruction attacks against models trained with and without DP-SGD. Models trained without DP were vulnerable to membership inference with attack AUC≈0.91. Under DP-SGD with ε≈4.0, attack AUC dropped to ≈0.58, indicating strong mitigation. However, DP degraded predictive metrics: payment fraud Tier-2 recall decreased by ~6 percentage points at strict ε budgets (ε≤1.0).

4.5 Trade-offs observed

Balancing latency, privacy, and interpretability required design concessions. The two-tier inference architecture was effective: it localized expensive privacy-preserving computations and deep explanations to suspicious cases, preserving latency for routine transactions. Explanation fidelity suffered under stricter DP budgets; to partially mitigate this, we published sensitivity intervals for attribution scores and offered sanitized exemplar aggregates instead of raw exemplars.

4.6 Case study vignettes

- *Fraud vignette*: A high-value transaction flagged by Tier-1 due to device velocity anomaly triggered Tier-2 analysis; the local counterfactual indicated that a change in device geolocation consistency would flip the prediction. Analyst UI showed exemplar aggregates of past frauds with similar device patterns, enabling a rapid decision to block and request verification.
- *Pharma vignette*: A candidate drug repurposing link between an approved small molecule and an inflammatory pathway was proposed. The explanation surfaced a two-hop subgraph connecting the drug to a kinase implicated in cytokine signaling; researchers used this to prioritize follow-up in vitro validation.

4.7 Limitations in evaluation

Our experiments used a mix of synthetic and public datasets constrained by privacy and access limitations. While simulations captured important dynamics (imbalance, drift, cross-site partitioning), production realities will introduce further heterogeneity and adversarial sophistication. The human evaluation cohorts were limited in size and biased toward collaborators; broader user studies are necessary to generalize findings.

4.8 Limitations and future directions

The framework is practical but not panacea. DP degrades model and explanation fidelity; HE and secure multi-party computations impose computational overhead; and cross-site collaboration demands legal and organizational alignment beyond technical solutions. Future work should explore causal explanations under privacy constraints, adaptive privacy budgeting that allocates fidelity dynamically where explanations are most valuable, and automated auditing tools that surface explanation inconsistencies introduced by privacy noise.

4.9 Deployment considerations and governance

Operationalizing this framework requires more than code:

- **Privacy governance:** Clear policies on privacy budgets, access controls, and audit trails.
- **Explainability governance:** Standards for explanation sufficiency per decision category (e.g., full explanation required for automated block vs. alert).
- **Monitoring:** Continuous telemetry for model drift, privacy budget consumption, and explanation fidelity.
- **Human oversight:** Human-in-the-loop policies and escalation pathways for ambiguous or high-impact cases.
- **Interdisciplinary collaboration:** ML engineers, privacy officers, domain experts, and legal/compliance teams must co-design thresholds and decide acceptable trade-offs.

4.10 Use-case dynamics

Real-time payment fraud detection

The system accepts continuous transaction streams. Tier-1 detects anomalous velocity, device inconsistencies, or sudden deviations from behavioral embeddings. Most transactions pass Tier-1 quickly. Flagged transactions route to Tier-2 for deeper sequence modeling and graph-based correlation (e.g., identifying networks of related accounts or device reuse). The analyst UI shows a concise local explanation: top contributing features, a counterfactual (what minimal change would avoid the block), exemplar aggregates of similar confirmed frauds, and a privacy confidence score. Analysts can confirm or dismiss alerts; labeled feedback feeds into retraining loops under the same privacy constraints.

Pharmaceutical network intelligence

Here, the system continually ingests literature-mined relations, assay results, and molecular data across several institutional silos. Secure aggregation or federated updates let sites jointly train GNNs that predict drug–target links without sharing raw assay data. Explanations emphasize subgraph paths, implicated pathways, and concept labels (e.g., “inflammatory signaling motif”), accompanied by sensitivity intervals showing how DP noise may alter path importance. Researchers use these outputs to prioritize in vitro tests and to generate mechanistic hypotheses.

V. CONCLUSION

This work presents a privacy-aware, explainable AI framework designed for multi-modal big data analytics in two high-stakes domains: real-time payment fraud detection and pharmaceutical network intelligence. By combining modality-aware encoders, privacy-preserving computation, a latency-conscious two-tier inference architecture, and a

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two-tier explanation strategy, the framework demonstrates that it is possible to produce timely, accurate, and interpretable outputs under practical privacy constraints.

Our results underscore several takeaways. First, hybrid modeling that separates fast screening from deep analysis allows systems to meet stringent latency needs while preserving the option for high-fidelity, privacy-protected scrutiny. Second, explanations are most actionable when they combine local attributions and counterfactuals for immediate triage with global, concept-based summaries for model governance and auditing. Third, privacy guarantees such as DP substantially reduce privacy leakage risk, but they also reduce the fidelity of both predictions and explanations; transparency about privacy budgets and explicit sensitivity reports are therefore essential for trustworthy deployment. Fourth, domain-specific modalities—sequence patterns in payments and subgraph motifs in biomedical networks—benefit from specialized encoders and explanation representations that map to analyst mental models.

We also reflect on ethical and governance implications. Systems that make consequential decisions must adopt rigorous testing, monitoring, and human oversight. Privacy-preserving techniques are necessary but not sufficient: technical guarantees must be complemented by operational safeguards, access controls, and compliance processes. Explainability is a human-centered endeavor: the quality of an explanation depends on whether it answers users' questions, fits their expertise level, and is presented with caveats about uncertainty and privacy-induced distortions.

Operationalizing the proposed framework requires investment in engineering, data governance, and cross-disciplinary collaboration among ML engineers, domain experts, privacy officers, and frontline analysts. Nevertheless, the evidence suggests that carefully designed systems can reduce investigation workloads, accelerate discovery, and provide defensible, auditable decision trails.

Modern enterprises and research groups ingest enormous, heterogeneous data streams: financial systems receive transaction sequences, device telemetry, geolocation and session logs; pharmaceutical networks aggregate chemical descriptors, high-throughput assay outputs, omics measurements, and literature-extracted relations. These modalities are valuable but bring three interlocking challenges.

First, decisions must often be made in (near) real time. Fraud detection requires millisecond-to-second responses to block suspicious transactions or trigger secondary authentication. In pharma intelligence, while discovery timelines are longer, researchers need fast triage of hypotheses from massive graph-structured data.

Second, privacy and compliance constraints are non-negotiable. Financial transaction data are protected by regulatory regimes and contractual obligations; biomedical data can carry personally identifiable or clinically sensitive information. Techniques such as differential privacy (DP), secure aggregation, federated learning, and selective encryption are increasingly necessary to enable cross-site collaboration without exposing raw data.

Third, opaque decisions undermine adoption. Deep models can outperform simpler methods, but without interpretable outputs they impede analyst triage, regulatory audits, and scientific hypothesis generation. Explanations must be both faithful enough to support decisions and designed to respect privacy mechanisms that may degrade explanation fidelity.

The central problem is therefore: how to design a single architectural approach that takes multimodal, streaming data; imposes provable privacy protections; produces timely and accurate predictions; and surfaces trustworthy explanations tailored to user needs.

A production-ready system for privacy-aware, explainable, multimodal analytics must deliberately trade and balance latency, privacy, and interpretability. By combining modular encoders, a latency-aware two-tier inference design, rigorous privacy mechanisms, and a layered explanation strategy that communicates uncertainty, organizations can build systems that both protect sensitive information and produce actionable, trustworthy insights for fraud analysts and biomedical researchers alike. The path forward lies in rigorous evaluation, strong governance, and close collaboration between technologists and domain stakeholders to ensure these systems meet real operational needs while respecting privacy and legal obligations.

VI. FUTURE WORK

1. **Stronger integration of causality**: Incorporating causal discovery and causal explanation methods could produce counterfactuals that better reflect interventions rather than correlational shifts.
2. **Adaptive privacy budgeting**: Research dynamic privacy budgets that allocate noise where the marginal utility is lowest and explanations where higher fidelity is critical.
3. **Robustness to adversaries**: Extend adversarial training and certification techniques for models under streaming and privacy constraints.
4. **Larger human studies**: Conduct broad, cross-organizational user studies to evaluate explanation utility, trust calibration, and operational impact.
5. **Automated explanation auditing**: Tools to automatically assess explanation fidelity under DP noise, and to flag explanations with high uncertainty for human review.

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