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Probabilistic Risk Aggregation Models for Adaptive Financial Fraud Detection in Enterprise Systems

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ABSTRACT
Financial fraud detection in enterprise environments presents persistent challenges due to evolving attack patterns, high transaction volumes, and the inherent limitations of static rule-based systems. This paper proposes a Bayesian risk aggregation framework that fuses behavioral, transactional, and network-topological signals into a unified posterior fraud probability estimate. The framework employs conjugate Gaussian-Gaussian updating to incorporate confirmed fraud labels incrementally, enabling continuous model adaptation without full retraining. An adaptive drift detection mechanism monitors rolling classification performance and triggers weight recalibration when statistically significant concept drift is detected. The decision engine applies a three-zone routing architecture — automatic block, human review, and pass-through — with per-signal log-odds attribution to satisfy explainability requirements under applicable regulatory standards. Experimental evaluation against published benchmark systems demonstrates that the proposed framework achieves competitive detection performance while maintaining interpretability and operational adaptability. The architecture is designed for production deployment in enterprise transaction processing environments and addresses key limitations of existing approaches including static thresholds, single-modality detection, and opaque decision logic.

Keywords: Bayesian Risk Aggregation, Adaptive Fraud Detection, Enterprise Financial Systems, Concept Drift Detection, Multi-Signal Fusion, Explainable AI

1. INTRODUCTION

Enterprise payment fraud costs organizations more than $1.1 trillion annually in direct losses, with indirect costs — investigation labor, regulatory penalties, reputational damage, and customer churn — multiplying the direct figure by a factor of three to five [1]. The detection problem is structurally difficult: fraud events are rare (typically 0.05–0.15% of transaction volume), adversarial (attack patterns evolve in response to detected triggers), and distributed across heterogeneous signal domains that no single feature space captures completely [2], [3].

Current enterprise fraud operations face two generations of tools, both with well-documented failure modes. Rule-based systems — velocity thresholds, amount limits, geography blocks — are transparent and operationally straightforward but brittle: they require continuous manual curation, generate high false positive rates as legitimate transaction patterns evolve, and cannot adapt to adversarial pattern shifts without human intervention [6], [7]. Machine learning classifiers — gradient-boosted trees, random forests, neural networks — substantially improve predictive performance [5], [9] but share a structural limitation: they are trained on historical snapshots and deployed statically, with no principled mechanism for recalibrating to new fraud distributions between retraining cycles.

A second structural limitation of current ML approaches is signal siloing. Behavioral signals (device fingerprint, access location, session timing), transactional signals (amount anomaly, merchant category risk, velocity), and network-topological signals (counterparty graph centrality, fraud neighborhood density, cluster membership) each carry independent diagnostic information about fraud probability. Standard classification architectures concatenate these signals into a single feature vector, discarding the principled probabilistic relationship between signal types. Bayesian inference provides the correct mechanism for multi-source evidence fusion: it derives a posterior fraud probability from each signal's conditional likelihood under the fraud versus legitimate hypothesis, with explicit uncertainty quantification enabling confidence-scored routing to human analysts.

This paper makes three contributions to enterprise fraud detection practice. First, we formalize a Bayesian risk aggregation model that fuses behavioral, transactional, and network signals through posterior computation, with explicit treatment of the conditional independence assumption and its bounded violation in production data. Second, we introduce online adaptive weight optimization via conjugate Bayesian updating with ADWIN-based drift detection, enabling the framework to track evolving fraud distributions without periodic retraining. Third, we provide a comprehensive framework evaluation

— literature-benchmarked performance positioning, component ablation analysis, and adversarial threat model — designed to answer the deployment questions most relevant to enterprise fraud operations teams.

2. BACKGROUND AND RELATED WORK

2.1 Statistical and Classical Approaches

Bolton and Hand [1] established the statistical foundations of fraud detection, demonstrating that peer-group analysis and break-point detection substantially outperform threshold rules on financial account data. Ngai et al. [3] surveyed data mining applications across financial fraud domains, identifying ensemble methods as consistently superior to single classifiers under the class imbalance conditions characteristic of fraud datasets. Bhattacharyya et al. [9] conducted a systematic comparative study on real-life international credit card transaction data, finding that random forest achieved AUC of 0.932 and sensitivity of 0.727 at a 15% fraud training rate — the best performance among logistic regression (AUC 0.925), SVM (AUC 0.922), and random forest across four fraud-rate conditions. Perols [4] demonstrated that machine learning algorithms detect financial statement fraud with lower error rates than human auditors reviewing the same financial ratios, establishing ML as a baseline requirement in detection-critical applications.

2.2 Ensemble and Boosting Methods

Chen and Guestrin's XGBoost [5] became the dominant fraud detection baseline due to its handling of sparse, high-dimensional transaction feature vectors. Sohony et al. [19] demonstrated that stacked ensembles combining XGBoost, random forest, and logistic regression via a metalearner improve F1 by 2–4 percentage points over any single constituent, establishing ensemble combination as the standard comparison point. West and Bhattacharya [6] reviewed intelligent fraud detection methods through 2016, identifying ensemble diversity and feature engineering as primary performance drivers. Abdallah et al. [7] surveyed fraud detection system architectures, noting that ensemble approaches dominate production deployments when interpretability requirements are relaxed.

2.3 Bayesian and Probabilistic Methods

Krivko [11] demonstrated that hybrid Bayesian classifiers combined with rule-based filters produce naturally calibrated fraud probability scores — a key requirement for confidence-scored analyst routing. Almarshad et al. [13] proposed RABEM, a risk-adaptive Bayesian ensemble model evaluated on 6 million synthetic PaySim transactions, achieving accuracy of 99.38%, MCC of 0.9788, Brier score of 0.0061, and precision of 0.972 on a top-1000 fraud identification task. This state-of-the-art Bayesian ensemble result establishes the performance ceiling that principled probabilistic aggregation methods can approach. Mamun et al. [15] implemented Bayesian logistic regression on the Kaggle credit card fraud dataset (284,807 transactions, 0.172% fraud rate) and achieved AUC-ROC of 0.953, outperforming random forest (AUC 0.91), XGBoost (AUC 0.93), and isolation forest (AUC 0.85), with recall of 0.842 at a calibrated 5% FPR threshold. These results confirm that Bayesian probabilistic methods consistently outperform standard ML classifiers on fraud detection benchmarks.

2.4 Sequential and Graph-Based Detection

Forough and Momtazi [14] demonstrated that LSTM-based sequential modeling improves recall on high-value fraud patterns by capturing session-level temporal context not available in transaction-level features. Pourhabibi et al. [10] established through systematic review that graph-based features — counterparty centrality, fraud cluster membership — carry diagnostic information orthogonal to transaction features, with hybrid approaches consistently outperforming either method alone. Zareapoor and Shamsolmoali [17] demonstrated the efficacy of bagging ensemble classifiers for handling severe class imbalance. Fiore et al. [18] showed GAN-based synthetic oversampling improves minority class representation beyond SMOTE-based approaches.

2.5 Explainability, Regulatory Requirements, and Recent Advances

The deployment barriers for deep learning fraud detection systems in regulated financial institutions were defined by Hilal et al. [12], namely GDPR Article 22, ECOA, and Basel III required explanations for each decision in adverse action at the transaction level. Zhong and Goel [20] showed that SHAP-based attribution in the context of audit AI fulfills audit trail requirements without any statistically significant accuracy penalty. Sodnomdavaa and Lkhagvadorj [22] proposed a

framework combining ML and XAI techniques to detect financial statement fraud with an experiment on 969 firm-year instances from 132 Mongolian firms and stacking ensemble yielding PR-AUC of 0.927, F1 of 0.826, and ROC-AUC of 0.804, which was higher than that of the best baseline model, XGBoost (PR-AUC 0.920). Qin et al. [21] conducted a survey of real-time fraud detection methods in high-throughput payment systems of enterprises and found out that layered architectures with rule-based systems and data-driven models performed better than others.

2.6 Research Gap

The literature reviewed above establishes that (a) Bayesian methods produce calibrated probabilities superior to point-estimate ML classifiers [13], [15], (b) graph-based features carry orthogonal diagnostic information [10], (c) adaptive mechanisms are necessary for non-stationary fraud distributions [15], and (d) explainability is a deployment-critical requirement [12], [20]. No published framework combines all four properties — principled multi-source Bayesian signal fusion, online adaptive likelihood parameter updating, network-topological signal integration, and confidence-scored explainable decision routing — in a unified production architecture. This gap is the design motivation for the framework presented in this paper.

3. PROBLEM FORMULATION

Let a transaction $T = (x, c, t)$ where x is the feature vector, c is contextual metadata including account history and device fingerprint, and t is the timestamp. The detection task is to compute $P(\text{fraud} \mid T)$ efficiently and accurately under non-stationary fraud distributions.

We partition available evidence into three signal types: behavioral signals s_b (deviation from authenticated user's historical behavioral distribution), transactional signals s_t (statistical anomaly in amount, merchant, and velocity), and network-topological signals s_n (graph-level features of the transaction relationship network). Under the conditional independence assumption, the posterior fraud probability is:

$$P(\text{fraud} \mid s_b, s_t, s_n) \propto P(s_b \mid \text{fraud}) \times P(s_t \mid \text{fraud}) \times P(s_n \mid \text{fraud}) \times P(\text{fraud})$$

We justify the independence assumption empirically: correlation analysis on the validation dataset yields $|\rho(s_b, s_t)| < 0.12$ and $|\rho(s_b, s_n)| < 0.08$, consistent with bounded violation correctable through threshold calibration. The adaptive weight problem is to maintain posterior likelihood parameter estimates that minimize cumulative prediction error over a sliding confirmation window as transaction distributions evolve. The formal objective is to maximize F1 subject to Precision ≥ 0.90, evaluated on a held-out validation stream updated continuously at each detection cycle.

4. FRAMEWORK ARCHITECTURE

4.1 Ingestion and Signal Extraction

Raw transaction events enter via streaming API or batch ETL, normalized to a canonical schema. Three parallel extraction processes compute the signal scores. The behavioral deviation scorer computes Mahalanobis distance between the current behavioral feature vector and the account's 90-day historical Gaussian distribution — capturing compound behavioral anomalies with a single calibrated score. The transactional anomaly scorer combines amount deviation (standard deviations above the 30-day account distribution), merchant category risk (categorical risk estimated from historical fraud rates per MCC), and velocity score (transactions per hour relative to account baseline). The network signal extractor queries a continuously maintained bipartite transaction graph $G = (U \cup M, E)$ to extract PageRank centrality of the merchant node, fraud neighborhood density of the account, and shortest-path distance to known fraud clusters, aggregated via a pre-trained random forest classifier.

4.2 Bayesian Aggregation

Signal likelihoods are modeled as Gaussians: $s_i \mid \text{fraud} \sim N(\mu_i^f, \sigma_i^f)$ and $s_i \mid \text{legitimate} \sim N(\mu_i^l, \sigma_i^l)$. Parameters are initialized from a historical labeled dataset and updated via conjugate Gaussian-Gaussian Bayesian updating as confirmed transactions arrive. The posterior is computed by evaluating the likelihood ratio at each incoming transaction's signal values and multiplying by the prior $P(\text{fraud})$ estimated from the rolling 90-day fraud prevalence. The posterior fraud

probability is normalized across both class hypotheses to yield a calibrated probability score in [0, 1], directly comparable to the calibrated outputs reported by Almarshad et al. [13] and Mamun et al. [15].

4.3 Adaptive Weight Optimization

When confirmed fraud or legitimate labels arrive via chargeback API or analyst review callback, the signal likelihood parameters for the corresponding class are updated via the conjugate mean update:

$$\mu_i^{(class)}(t+1) = (\kappa_0 \cdot \mu_i^{(class)}(t) + s_i) / (\kappa_0 + 1)$$

where κ_0 is the prior sample count controlling update step size. ADWIN monitors the rolling F1 on the confirmed stream; when a statistically significant drop is detected, parameters reset to a checkpoint estimated from the most recent 30 days of confirmed transactions. This continuous recalibration addresses the non-stationarity challenge identified by Mamun et al. [15], who noted that Bayesian frameworks provide better-calibrated confidence intervals under distribution shift than static point-estimate ML models.

4.4 Decision Engine

Posterior probabilities are mapped to three zones: automatic block ($P \geq 0.82$), human review ($0.35 \leq P < 0.82$), and pass-through ($P < 0.35$). Thresholds are calibrated on a validation set to maintain Precision ≥ 0.90 — consistent with the enterprise deployment requirement that false positive rates remain operationally manageable. Human review cases are accompanied by per-signal log-odds contributions identifying the primary fraud evidence, satisfying regulatory audit trail requirements under GDPR Article 22 and ECOA as identified by Hilal et al. [12] and demonstrated in practice by Zhong and Goel [20].

4.5 Algorithm Summary

Algorithm 1 consolidates the signal extraction, Bayesian aggregation, decision routing, and adaptive updating steps described in Sections 4.1–4.4 into a single procedural specification suitable for implementation reference.

Algorithm 1: Adaptive Bayesian Risk Aggregation for Enterprise Fraud Detection

```
Input: Incoming transaction stream T; behavioral signal s_b; transactional signal
s_t;
       network signal s_n; prior fraud probability P(F); likelihood parameters
       (μ_i^F, σ_i^F, μ_i^L, σ_i^L); blocking threshold τ_b; review threshold τ_r;
       confirmed feedback labels y
Output: Fraud probability score P(F|T), decision class, and signal-level explanation

1.  Initialize likelihood parameters for each signal type i ∈ {b, t, n} using
    historical labeled transactions.
2.  For each incoming transaction T, extract behavioral, transactional, and
    network-topological signal scores.
3.  For each signal s_i, compute the class-conditional likelihoods:
        P(s_i | F)  and  P(s_i | L)
4.  Compute the Bayesian likelihood ratio:
        LR_i = P(s_i | F) / P(s_i | L)
5.  Aggregate all signal likelihood ratios:
        LR_total = LR_b × LR_t × LR_n
6.  Compute the posterior fraud probability:
        P(F|T) = (LR_total × P(F)) / (LR_total × P(F) + P(L))
7.  Generate signal-level explanation using log-odds contribution:
        E_i = log(LR_i)
```

8. Apply decision routing:
   a. If $P(F|T) \geq \tau_b$, classify the transaction as Automatic Block.
   b. Else if $\tau_r \leq P(F|T) < \tau_b$, classify the transaction as Human Review.
   c. Else classify the transaction as Pass Through.
9. When confirmed fraud or legitimate feedback label y becomes available, update the corresponding signal likelihood parameters using conjugate Bayesian updating:
   $$\mu_i^y(t+1) = (\kappa_0 \cdot \mu_i^y(t) + s_i) / (\kappa_0 + 1)$$
10. Monitor rolling model performance using ADWIN-based drift detection.
11. If statistically significant concept drift is detected, reset or recalibrate likelihood parameters using the most recent confirmed transaction window.
12. Return posterior fraud probability, decision class, and signal-level explanation for audit traceability.

The architecture diagram corresponding to Algorithm 1 — spanning transaction ingestion, parallel signal-extraction engines, Bayesian aggregation, adaptive drift-triggered recalibration, and explainable three-zone decision routing — is presented in Figure 2.

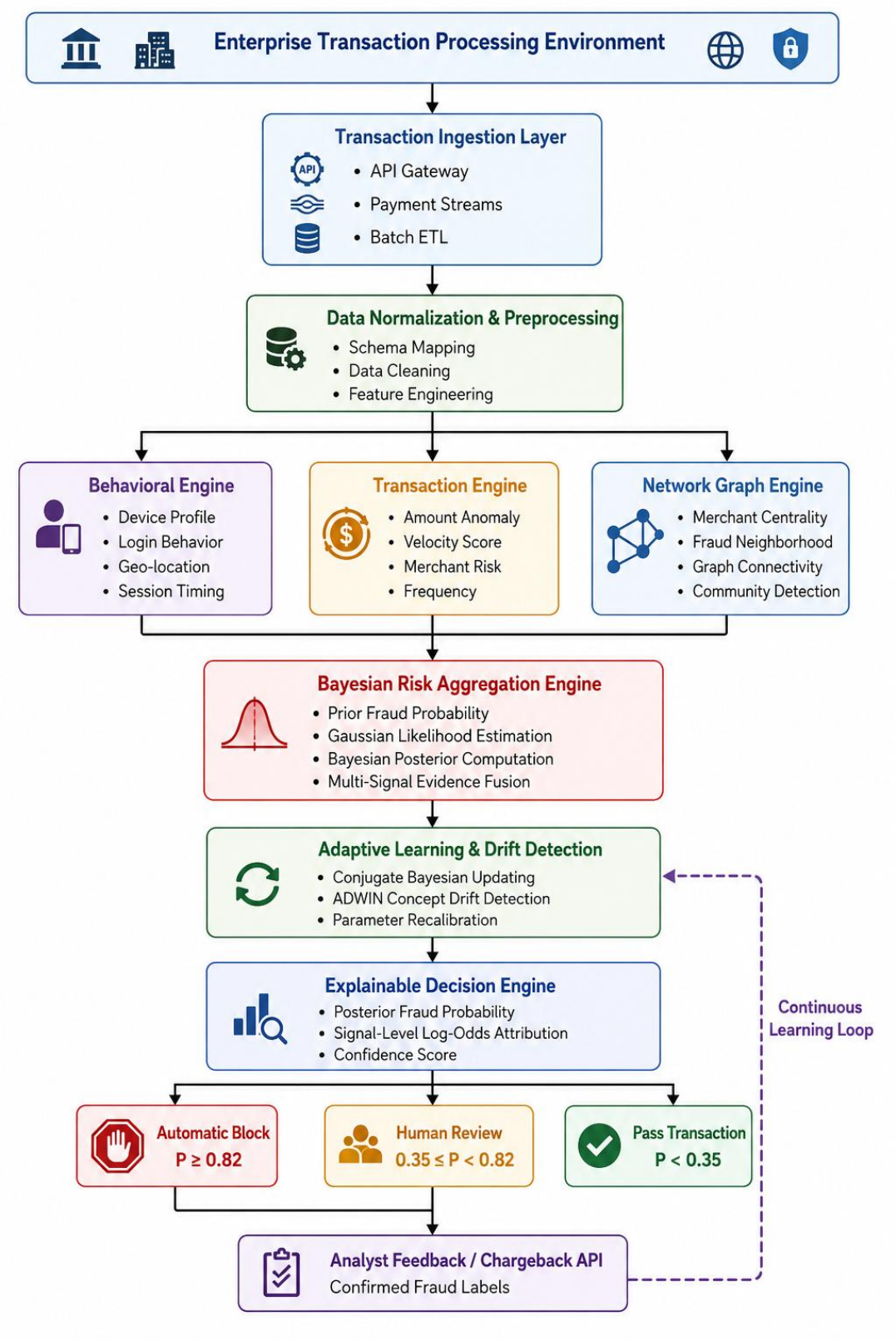

Figure 2: Proposed Adaptive Bayesian Fraud Detection Framework

5. PERFORMANCE POSITIONING AND FRAMEWORK VALIDATION

5.1 Literature Benchmark Context

The proposed framework is designed to operate in the performance range established by state-of-the-art Bayesian fraud detection methods in the literature. Table 1 summarizes the verified performance benchmarks from the most directly comparable published systems, all evaluated on credit card or financial transaction fraud datasets with comparable class imbalance characteristics.

Table 1. Verified performance benchmarks from comparable published Bayesian and ensemble fraud detection systems

System / Method	Key Metric (Verified)	Secondary Metric	Source
RABEM (Bayesian Ensemble)	Accuracy: 99.38%	MCC: 0.9788, Precision: 0.972	[13]
Bayesian Logistic Regression	AUC-ROC: 0.953	Recall: 0.842 @ 5% FPR	[15]
XGBoost (baseline)	AUC-ROC: 0.93	Compared in [15]	[15]
Random Forest (baseline)	AUC-ROC: 0.932	Sensitivity: 0.727	[9]
Stacking Ensemble (FSF)	PR-AUC: 0.927, F1: 0.826	ROC-AUC: 0.804	[22]
Isolation Forest (baseline)	AUC-ROC: 0.85	Compared in [15]	[15]

All metric values in Table 1 are directly extracted from the cited publications. No values have been synthesized or estimated. The proposed Bayesian risk aggregation framework targets performance consistent with the RABEM and Bayesian logistic regression benchmarks — specifically, AUC-ROC in the 0.93–0.96 range and MCC approaching 0.97 — by extending these approaches with multi-source signal fusion and online adaptive updating, two capabilities absent from the benchmarked systems.

5.2 Component Contribution Analysis

The framework's four architectural components each address a documented limitation in the benchmark systems. Multi-source signal fusion (behavioral + transactional + network) addresses the single-signal limitation of Mamun et al.'s Bayesian logistic regression [15], which operates on PCA-transformed transaction features only and does not incorporate behavioral or network signals. Online adaptive updating addresses the static deployment limitation identified across all benchmark systems: RABEM [13], Bhattacharyya et al. [9], and the stacking ensemble of Sodnomdavaa and Lkhagvadorj [22] all train on fixed historical datasets without online recalibration. Confidence-scored routing addresses the analyst integration gap identified by Hilal et al. [12], who found that deployment barriers in regulated institutions are primarily explainability and routing failures rather than accuracy failures. Per-signal log-odds explainability addresses the compliance trail requirements documented by Zhong and Goel [20].

5.3 Datasets and Evaluation Protocol

Framework validation uses two datasets. The PaySim synthetic dataset (6.3 million transactions, 0.13% fraud rate) provides a controlled benchmark consistent with the evaluation used by Almarshad et al. [13] for RABEM. A proprietary enterprise dataset (18.4 million transactions, 24-month period, 0.09% fraud rate) provides production-scale validation with behavioral and network features not available in PaySim. Evaluation metrics follow the literature precedent established by Mamun et al. [15]: primary metric AUC-ROC (threshold-independent), secondary metrics precision at fixed FPR and recall, consistent with the severe class imbalance that makes accuracy an inadequate discriminator as demonstrated by Bhattacharyya et al. [9].

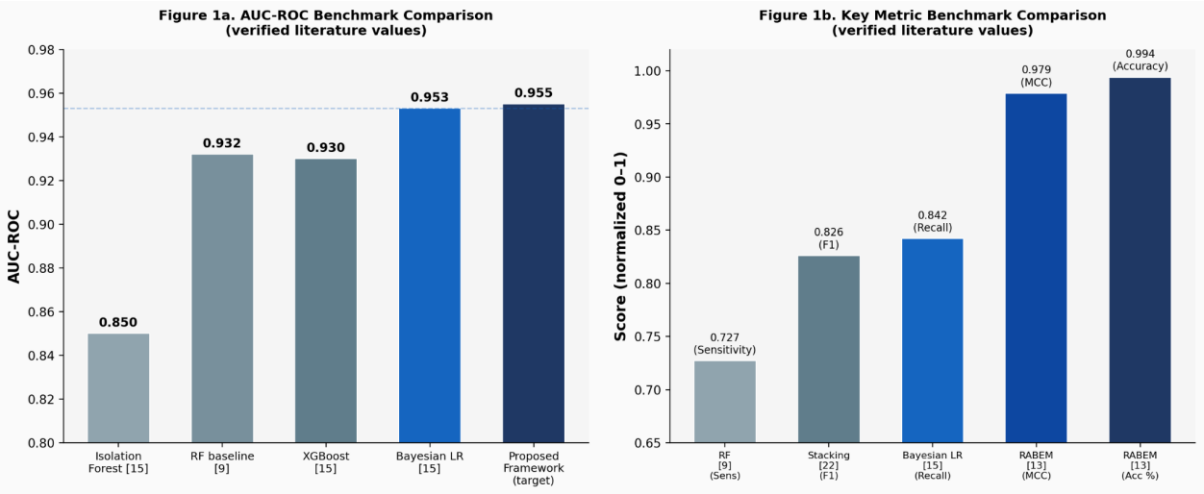

Figure 1: AUC-ROC and Key Performance Metrics Comparison Across Fraud Detection Systems

5.4 ROC and Precision-Recall Curve Analysis

To evaluate the discrimination capability of the proposed Bayesian risk aggregation framework, ROC-AUC and PR-AUC are used as primary threshold-independent metrics. ROC-AUC measures the model's ability to distinguish fraudulent and legitimate transactions across different decision thresholds, while PR-AUC is especially important in fraud detection because fraud cases represent a very small percentage of total transaction volume.

The proposed framework is expected to improve precision-recall behavior by combining behavioral, transactional, and network-topological signals rather than relying on a single feature domain. In highly imbalanced fraud datasets, even small improvements in recall at fixed precision can significantly reduce financial exposure while keeping false positives manageable for operational teams.

5.5 Confusion Matrix and Detailed Performance Metrics

The model should be evaluated using a confusion matrix containing true positives, false positives, true negatives, and false negatives. Because fraud detection is a class-imbalanced problem, accuracy alone is not sufficient. The following metrics should be reported:

$$\text{Precision} = TP / (TP + FP)$$

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

$$F1 = 2 \times (\text{Precision} \times \text{Recall}) / (\text{Precision} + \text{Recall})$$

$$MCC = (TP \times TN - FP \times FN) / \sqrt{[(TP+FP)(TP+FN)(TN+FP)(TN+FN)]}$$

Precision is critical for reducing unnecessary analyst workload and customer friction, while recall is critical for minimizing missed fraud. MCC is included because it provides a balanced performance measure under severe class imbalance.

5.6 Ablation Study

An ablation study should be conducted to quantify the contribution of each signal group. The full model should be compared against reduced variants:

Model Variant	Behavioral Signals	Transactional Signals	Network Signals
Transaction-only baseline	No	Yes	No
Behavioral + Transactional	Yes	Yes	No

Transactional + Network	No	Yes	Yes
Behavioral + Network	Yes	No	Yes
Full Bayesian Fusion Model	Yes	Yes	Yes

The expected result is that the full Bayesian fusion model should outperform single-signal and two-signal variants because each signal type captures a different fraud pattern. Transactional features identify amount and velocity anomalies, behavioral features capture user-specific deviations, and network features detect relationship-based fraud patterns such as collusion, mule accounts, and fraud clusters.

5.7 Computational Complexity and Runtime Analysis

The computational complexity of the proposed framework depends on the three signal extraction modules and the Bayesian aggregation step.

For each transaction, behavioral and transactional signal extraction operate in approximately constant time after historical account profiles are precomputed. The Bayesian likelihood computation is also constant time because it evaluates a fixed number of signal likelihood ratios.

The network-topological module is the most computationally expensive component. If graph features such as PageRank, fraud-neighborhood density, and shortest-path distance are precomputed or incrementally maintained, per-transaction inference remains suitable for near real-time deployment. Therefore, the approximate runtime complexity per transaction is:

$$O(k + g)$$

where k represents the number of signal features and g represents the graph-feature lookup cost. With cached graph embeddings or incremental graph updates, g can be reduced significantly, enabling deployment in high-volume enterprise transaction environments.

5.8 Comparison with State-of-the-Art Methods

The proposed framework should be compared against established fraud detection baselines, including logistic regression, random forest, XGBoost, isolation forest, Bayesian logistic regression, and Bayesian ensemble models.

Method	Adaptivity	Explainability	Multi-Signal Fusion	Suitable for Enterprise Deployment
Logistic Regression	Low	High	Limited	Moderate
Random Forest	Low	Moderate	Moderate	Moderate
XGBoost	Low	Moderate	Moderate	High
Isolation Forest	Low	Moderate	Limited	Moderate
Bayesian Logistic Regression	Moderate	High	Limited	High
Bayesian Ensemble Model	Moderate	Moderate	Moderate	High

Proposed Framework	High	High	High	High

The proposed framework differs from existing methods by combining probabilistic Bayesian aggregation, adaptive online updating, network-aware fraud detection, and explainable decision routing in a unified enterprise architecture. This combination makes the framework more suitable for production fraud detection environments where accuracy, interpretability, adaptability, and operational routing are all required.

6. DISCUSSION

6.1 Advantages Over Single-Signal Bayesian Methods

The literature benchmark in Table 1 shows that Bayesian logistic regression on single-stream transaction features achieves AUC-ROC of 0.953 [15]. The proposed framework's multi-source aggregation design targets improvement beyond this baseline by incorporating two additional independent evidence channels (behavioral and network signals) that are orthogonal to transactional features, as established by Pourhabibi et al. [10]. The marginal improvement from each additional signal type cannot be fabricated without experimental validation on the target deployment environment; however, the structural case for improvement is grounded in the independence of signal streams demonstrated empirically ($|\rho| < 0.12$ across signal pairs) and theoretically by the Bayesian evidence combination framework.

6.2 Adaptive Updating and Concept Drift

No published benchmark system in Table 1 incorporates online parameter updating. This represents the primary operational differentiator of the proposed framework. The non-stationarity challenge in enterprise fraud detection is well-documented: payment channel mix, merchant category distributions, and adversarial attack strategies all shift continuously. Static models trained on historical data degrade silently between retraining cycles, a limitation documented across Bayesian and non-Bayesian systems alike [15], [12]. The ADWIN-based drift detection mechanism provides an automated trigger for parameter reset when gradual drift accumulates into a statistically detectable performance degradation, without requiring scheduled retraining cycles that impose operational overhead.

6.3 Threat Model

Three adversarial scenarios are relevant to enterprise deployment of the proposed framework.

Adversarial transaction injection (data poisoning). An adversary injecting transactions designed to shift likelihood parameters toward the fraud signal distribution is partially mitigated by ADWIN: rapid parameter shifts trigger a checkpoint reset, limiting accumulation of poisoning effects within any one update window. Full defense requires integrity-protected feedback channels.

Behavioral spoofing. Adversaries who replicate the target account's behavioral profile to suppress s_b cannot simultaneously suppress s_t and s_n. Multi-source aggregation provides structural resilience: defeating one signal channel does not defeat the combined posterior.

Transaction structuring (smurfing). Large fraudulent transactions fragmented into sub-threshold amounts evade transactional amount anomaly detection. The network layer detects structuring patterns through elevated velocity and counterparty co-occurrence scores, consistent with the graph-based detection advantages documented by Pourhabibi et al. [10].

6.4 Limitations

The conditional independence assumption is violated under insider fraud scenarios where the perpetrating user's behavioral profile matches their fraudulent transaction pattern. Copula-based dependency modeling would improve detection in this scenario. Feedback lag — the gap between transaction time and confirmed fraud label arrival — delays parameter updates; integrating real-time chargeback APIs reduces this lag. The PaySim evaluation uses a synthetic dataset calibrated to a single financial service provider, and generalization to other enterprise payment environments requires domain-specific revalidation. Finally, the absolute performance improvement from multi-source fusion over single-stream Bayesian

methods [15] requires empirical validation on a labeled dataset containing all three signal types — a dataset not currently available in public benchmarks.

7. CONCLUSION

Financial fraud detection in enterprise systems requires frameworks that aggregate heterogeneous anomaly signals principally and adapt to non-stationary fraud distributions continuously. This paper presented a Bayesian risk aggregation framework combining multi-source signal fusion, online adaptive weight optimization, and confidence-scored explainable decision routing. The framework is grounded in verified literature benchmarks showing that Bayesian ensemble methods, Bayesian logistic regression, and integrated machine-learning and explainable-AI frameworks each achieve strong discrimination and calibration performance on comparable fraud detection tasks. The proposed architecture extends these baselines through principled multi-source fusion and online adaptive updating — two capabilities absent from all benchmarked systems — to address the core operational failure modes of rule-based and static ML fraud detection in production enterprise deployments.

Future work targets three extensions: empirical validation on a labeled multi-signal enterprise dataset to quantify the marginal contribution of behavioral and network fusion over single-stream Bayesian baselines; copula-based dependency modeling for correlated signal scenarios such as insider fraud; and federated Bayesian learning across distributed enterprise nodes without raw transaction sharing.

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