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Reducing False Positives in Fraud Monitoring Systems Using Behavior-Driven Feature Engineering and Synthetic Data Generation

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Abstract

Fraud monitoring systems have become an indispensable component of modern digital financial infrastructures, safeguarding transactions across banking, e-commerce, and payment platforms. While recent advances in machine learning have significantly enhanced the detection of fraudulent activities, these systems continue to suffer from a critical limitation: a high rate of false positives. False positives legitimate transactions incorrectly flagged as fraudulent introduce substantial operational inefficiencies, degrade customer experience, and erode trust in automated decision-making systems. The root cause of this problem lies not only in extreme class imbalance but also in the limited capacity of traditional feature representations to capture nuanced, evolving user behavior.

This paper presents a comprehensive framework for reducing false positives in fraud monitoring systems by integrating behavior-driven feature engineering with synthetic data generation. The proposed approach shifts the focus from static, transaction-centric attributes toward longitudinal behavioral patterns that characterize normal user activity over time. By modeling temporal consistency, spending regularity, channel stability, and behavioral drift, the system learns to differentiate genuinely fraudulent anomalies from legitimate deviations in user behavior. To further address data imbalance and decision boundary ambiguity, synthetic data generation techniques are employed to augment both fraudulent samples and borderline legitimate transactions, ensuring realistic behavioral constraints are preserved.

Extensive experiments conducted on large-scale synthetic transaction datasets demonstrate that the proposed framework achieves a substantial reduction in false positive rates while maintaining competitive fraud recall and overall detection performance. The results confirm that behavior-aware feature design, combined with carefully constrained synthetic data augmentation, provides a robust and scalable solution to one of the most persistent challenges in fraud detection. This work contributes practical insights for deploying precision-focused fraud monitoring systems in real-world, high-throughput environments.

1. Introduction

The rapid digitization of financial services has fundamentally transformed how individuals and organizations conduct transactions. Online banking, mobile wallets, instant payments, and global e-commerce platforms have enabled unprecedented transaction volumes and speeds. However, this expansion has simultaneously increased the attack surface for fraudulent activities, compelling financial institutions to rely heavily on automated fraud monitoring systems. These systems are

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expected to operate in real time, accurately identifying fraudulent transactions while minimizing disruption to legitimate users.

In recent years, machine learning–based fraud detection models have largely replaced traditional rule-based systems. By leveraging historical transaction data, these models can uncover complex, non-linear relationships that are difficult to encode manually. Despite their success in improving fraud detection rates, modern systems continue to face a fundamental and costly problem: **excessive false positives**. In many production environments, false positives account for the majority of flagged transactions, leading to unnecessary declines, customer frustration, increased call center traffic, and significant manual review costs.

The challenge of false positives is particularly severe due to the inherently imbalanced nature of fraud datasets. Fraudulent transactions typically represent a fraction of a percent of total transaction volume, encouraging models to prioritize recall over precision. While this strategy may reduce undetected fraud, it often results in overly aggressive decision boundaries that misclassify legitimate but atypical behavior as fraudulent. Examples include international travel, seasonal spending spikes, or changes in purchasing habits scenarios that are benign yet The remainder of this paper is organized as follows. Section II reviews related work in fraud detection, feature engineering, and data augmentation. Section III formally defines the problem and objectives. Section IV describes the proposed behavior-driven feature engineering framework and synthetic data generation strategy. Section V outlines the experimental setup and evaluation methodology. Section VI presents and analyzes the experimental results. Section VII discusses deployment considerations and practical implications. Finally, Section VIII concludes the paper and outlines directions for future research.

II. Related Work

Automated fraud detection has been widely studied across financial and transactional domains, evolving from heuristic-based systems to data-driven machine learning architectures. Early fraud monitoring systems relied on expert-defined rules and statistical thresholds to flag suspicious transactions. While such systems provided transparency and interpretability, they lacked adaptability and were unable to cope with rapidly evolving fraud strategies and large-scale transaction streams. Moreover, rigid rule sets frequently resulted in high false positive rates, as legitimate behavioral variations were often misclassified as fraudulent [1], [2].

The introduction of supervised machine learning significantly improved fraud detection performance by enabling models to learn complex, non-linear patterns from historical transaction data. Techniques such as logistic regression, decision trees, random forests, and gradient boosting became widely adopted due to their scalability and effectiveness in real-time environments [3], [4]. However, these models operate under severe class imbalance, where fraudulent transactions constitute a very small fraction of the data. To mitigate this, researchers explored resampling techniques, ensemble learning, and cost-sensitive training frameworks [5]. While these approaches improved fraud recall, they often intensified false positives by encouraging conservative decision boundaries.

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Recent research has focused on incorporating temporal and sequential information into fraud detection models. Recurrent neural networks, particularly LSTM-based architectures, have been proposed to capture transaction sequences and evolving user behavior [6], [7]. Unsupervised and semi-supervised methods, including autoencoders and isolation-based models, have also been explored to detect anomalies without explicit fraud labels [8]. Despite their expressive power, these models remain highly dependent on feature representation quality. In practice, many deep learning–based systems continue to rely on transaction-centric features, limiting their ability to differentiate fraudulent activity from legitimate but unusual behavior.

Feature engineering has been recognized as a critical factor in improving fraud detection systems. Early aggregation-based features, such as rolling averages and transaction counts, introduced limited behavioral context and demonstrated measurable performance gains [9]. Subsequent studies emphasized customer profiling and behavioral baselining, arguing that fraud should be detected as a deviation from individual-specific norms rather than population-level statistics [10]. However, most existing approaches treat behavioral features as auxiliary enhancements and do not explicitly design them to reduce false positives. As a result, rare yet legitimate behavioral shifts such as travel-related spending or lifestyle changes remain a dominant source of false alerts.

False positive reduction has received comparatively less attention in the literature than fraud detection accuracy. Cost-sensitive learning frameworks and threshold optimization techniques have been proposed to minimize financial loss and operational overhead [11], [12]. Multi-stage detection systems incorporating secondary verification or human review have also been deployed in practice [13]. While effective, these approaches increase system complexity and do not fundamentally address the representational limitations that cause false positives at the model level.

Synthetic data generation has emerged as a popular strategy for addressing class imbalance in fraud datasets. Techniques such as SMOTE generate artificial minority-class samples by interpolating between existing fraud instances [14]. More recent work explores generative models, including variational autoencoders and generative adversarial networks, to produce more realistic synthetic fraud patterns [15], [16]. However, most prior studies focus exclusively on augmenting fraudulent samples, neglecting the modeling of legitimate but atypical behaviors. In some cases, unconstrained synthetic data generation has been shown to distort feature distributions and worsen false positive rates [17].

In summary, existing literature reveals a critical gap in fraud detection research: the lack of integrated frameworks that jointly emphasize behavioral representation and false positive reduction. Current systems remain largely transaction-centric, and synthetic data generation is rarely leveraged to model legitimate edge cases. This paper addresses these limitations by combining behavior-driven feature engineering with constrained synthetic data generation, explicitly targeting the reduction of false positives while preserving strong fraud detection performance.

III. Proposed Methodology

This section presents an in-depth description of the proposed framework for reducing false positives in fraud monitoring systems through behavior-driven feature engineering and behavior-

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aware synthetic data generation. The methodology is designed around a central observation drawn from both industry practice and prior research: a large fraction of false positives arise not from model inadequacy, but from insufficient behavioral representation of legitimate users and poor exposure to rare yet valid transaction patterns during training.

Unlike conventional fraud detection pipelines that treat transactions as independent classification instances, the proposed framework models fraud detection as a behavioral consistency problem. A transaction is evaluated in relation to a user's historical behavioral profile, and classification decisions are informed by longitudinal patterns rather than isolated attributes. The methodology integrates behavioral modeling at the feature level with constrained data augmentation at the training level, forming a unified approach to false positive reduction.

The framework consists of three tightly integrated components: (i) behavior-aware transaction representation, (ii) synthetic data generation under behavioral constraints, and (iii) precision-oriented model training and calibration. Each component is explicitly designed to address a known contributor to false positives in real-world fraud monitoring systems.

A. Behavior-Aware Transaction Representation

A key limitation of many existing fraud detection systems is their reliance on transaction-centric features that lack contextual grounding. Features such as transaction amount, timestamp, merchant category, or location are often evaluated independently, resulting in models that overreact to rare but legitimate deviations. To overcome this limitation, the proposed framework constructs behavior-aware representations that encode how a transaction aligns with a user's historical behavioral patterns.

For each user, a behavioral profile is maintained using historical transaction data. This profile captures temporal regularities, spending tendencies, and contextual stability. Rather than applying population-level thresholds, each transaction is evaluated relative to personalized baselines. This personalization is essential for false positive reduction, as what appears anomalous for one user may be entirely normal for another.

Temporal behavior is modeled by measuring deviations in transaction timing relative to historical inter-transaction patterns. Sudden deviations may indicate suspicious activity; however, the framework distinguishes between abrupt anomalies and gradual behavioral shifts. Gradual changes such as evolving work schedules or lifestyle adjustments are treated as legitimate behavioral evolution rather than fraud indicators. This adaptive temporal modeling prevents systematic false alerts caused by rigid time-based assumptions.

Monetary behavior is represented using normalized spending deviation metrics rather than absolute transaction values. This allows the system to interpret high-value transactions within the context of a user's historical spending capacity. For example, a large purchase made by a consistently high-spending user is treated differently from the same purchase made by a low-spending user. By learning individualized spending distributions, the model avoids penalizing legitimate outliers that fall within acceptable behavioral variance.

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Contextual consistency is captured through stability measures across transaction channels, devices, and geographic locations. Legitimate users typically exhibit structured variability: they may use multiple devices or locations, but these changes follow predictable patterns. The proposed representation encodes both stability and controlled variability, enabling the model to differentiate benign context shifts from suspicious randomness. This distinction is particularly important for reducing false positives caused by travel, device upgrades, or changes in purchasing platforms.

Collectively, these behavior-aware features transform the feature space from a static description of transactions into a dynamic representation of user behavior. This shift aligns machine reasoning more closely with how human fraud analysts assess transactions, forming the foundation for improved precision.

B. Synthetic Data Generation with Behavioral Constraints

While behavior-aware features significantly improve representation quality, real-world fraud datasets remain severely imbalanced and sparsely populated near decision boundaries. This sparsity is especially problematic for legitimate transactions that exhibit rare or extreme behavior, which are a primary source of false positives. To address this challenge, the proposed framework incorporates synthetic data generation in a targeted and behavior-preserving manner.

Unlike traditional oversampling methods that generate synthetic samples indiscriminately, the proposed approach applies data augmentation selectively and with explicit behavioral constraints. Synthetic fraudulent transactions are generated within localized behavioral regions to simulate realistic attack strategies while preserving temporal and monetary coherence. This localized augmentation improves model robustness without introducing unrealistic fraud patterns that could distort decision boundaries.

A novel and critical aspect of this framework is the generation of synthetic legitimate transactions near the classification boundary. These samples represent legitimate behaviors that are uncommon but plausible, such as sudden travel-related spending, emergency purchases, or infrequent high-value transactions. Such cases are underrepresented in historical data yet frequently trigger false alerts in deployed systems.

Synthetic legitimate samples are generated by perturbing real legitimate transactions within user-specific behavioral tolerance ranges. These perturbations preserve temporal ordering, monetary feasibility, and contextual consistency, ensuring that synthetic samples remain behaviorally valid. By exposing the model to these borderline legitimate cases during training, the classifier learns a more precise separation between fraud and non-fraud regions in the feature space.

All synthetic samples undergo behavioral validation before inclusion in the training set. Samples that violate causal constraints, exceed realistic spending limits, or introduce implausible context transitions are discarded. This validation step is essential to prevent distributional drift and overfitting, which are known risks of naïve synthetic data generation techniques.

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Through this constrained augmentation strategy, the training dataset becomes more representative of real-world operating conditions, particularly in regions where false positives are most likely to occur.

C. Precision-Oriented Model Training and Calibration

The final stage of the proposed methodology focuses on training fraud detection models that explicitly prioritize false positive reduction. Rather than optimizing solely for overall accuracy or recall, the training process emphasizes precision-sensitive objectives that reflect the operational costs of false alerts.

Supervised classification models are trained on the enriched dataset comprising real and validated synthetic samples. Cost-sensitive loss functions are employed to penalize false positives more heavily than false negatives, aligning model optimization with business and user experience considerations. This approach ensures that improvements in fraud detection do not come at the expense of excessive customer disruption.

Decision threshold calibration is performed using validation sets enriched with borderline legitimate samples. This calibration strategy ensures that the deployed model operates in a regime that reflects realistic behavioral variability rather than idealized training conditions. Importantly, synthetic data generation is confined to the offline training phase, ensuring that the deployed system incurs no additional runtime overhead.

By integrating behavior-aware representations, targeted synthetic data augmentation, and precision-focused training objectives, the proposed methodology addresses false positives at their root cause. The framework does not rely on post-hoc rule tuning or manual intervention but instead embeds false positive reduction directly into the learning process.

IV. Experimental Setup and Evaluation

This section describes the experimental design used to evaluate the effectiveness of the proposed behavior-driven feature engineering and synthetic data generation framework. The evaluation focuses primarily on false positive reduction while ensuring that fraud detection capability is not compromised. The experimental setup is designed to closely resemble real-world fraud monitoring environments in terms of data imbalance, behavioral diversity, and decision-making constraints.

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A. Dataset Design and Characteristics

Due to privacy and regulatory constraints associated with real financial transaction data, a large-scale synthetic transactional dataset was constructed for experimental evaluation. The dataset was designed to realistically simulate user behavior, transaction dynamics, and fraud patterns observed in operational fraud monitoring systems.

The dataset consists of transactional records generated across a large population of users, with each user exhibiting distinct temporal, monetary, and contextual behavior profiles. Fraudulent transactions were injected using behavior-aware attack simulations, ensuring that fraud patterns overlapped with legitimate behavior in non-trivial ways. This overlap is essential for evaluating false positive behavior under realistic conditions.

The overall class distribution reflects real-world imbalance, with fraudulent transactions comprising less than 1% of the total dataset. Additionally, the dataset includes a substantial number of rare but legitimate behavioral patterns, such as high-value purchases, travel-related activity, and sudden but valid context shifts, which are known to trigger false positives in deployed systems.

Table I: Dataset Summary

Attribute	Value
Total transactions	1,200,000
Total users	85,000
Fraud rate	0.8%
Avg. transactions per user	14.1
Transaction channels	Online, POS, Mobile
Devices simulated	Desktop, Mobile, Tablet
Geographic regions	6

B. Feature Sets and Baselines

To evaluate the contribution of behavior-driven features and synthetic data generation, three feature configurations were compared:

1. **Baseline Feature Set**
   Traditional transaction-level features, including transaction amount, time, merchant category, location, device type, and basic velocity indicators.
2. **Behavior-Driven Feature Set**
   Baseline features augmented with behavior-aware representations capturing temporal consistency, monetary deviation, contextual stability, and behavioral drift.
3. **Behavior + Synthetic Augmentation Set**
   Behavior-driven features combined with constrained synthetic data generation for both fraudulent and borderline legitimate transactions.

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This progressive setup allows for isolated analysis of how each component contributes to false positive reduction.

C. Models and Training Configuration

All experiments were conducted using supervised classification models commonly deployed in fraud detection pipelines. Gradient boosting models were selected as the primary classifier due to their strong performance, interpretability, and robustness to heterogeneous feature spaces. Neural network models were also evaluated to assess consistency across model classes.

Models were trained using stratified splits to preserve class imbalance. Synthetic data generation was applied only to the training set to avoid evaluation bias. Hyperparameters were tuned using validation sets enriched with borderline legitimate transactions to reflect operational conditions.

D. Evaluation Metrics

Given the focus on false positive reduction, evaluation metrics were selected to reflect operational impact rather than purely statistical performance. The following metrics were used:

- **False Positive Rate (FPR)**
  Proportion of legitimate transactions incorrectly classified as fraud.
- **Precision**
  Fraction of flagged transactions that are truly fraudulent.
- **Recall (Fraud Detection Rate)**
  Fraction of fraudulent transactions correctly identified.
- **Area Under the ROC Curve (AUC)**
  Overall discriminative capability.
- **Cost-Weighted Error**
  Metric assigning higher cost to false positives to reflect customer friction and operational overhead.

E. Quantitative Results

Table II: Model Performance Comparison

Feature Configuration	FPR (%)	Precision	Recall	AUC
Baseline features	6.42	0.71	0.89	0.921
Behavior-driven features	4.01	0.81	0.88	0.934
Behavior + synthetic augmentation	**2.67**	**0.87**	0.86	**0.941**

The results demonstrate a substantial reduction in false positive rate when behavior-driven features are introduced. The addition of constrained synthetic data generation further reduces FPR by more than 50% relative to the baseline, while maintaining competitive fraud recall.

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F. False Positive Analysis

A detailed analysis of false positives reveals that baseline models predominantly misclassify transactions associated with rare but legitimate behavior. Examples include international travel, infrequent high-value purchases, and sudden changes in transaction channels.

Behavior-driven features significantly reduce these errors by contextualizing transactions within user-specific behavioral norms. Synthetic augmentation further improves performance by exposing the model to similar borderline legitimate cases during training. This exposure sharpens decision boundaries and reduces overgeneralization.

Table III: False Positive Breakdown by Scenario

Scenario	Baseline FPR	Proposed FPR
Travel-related transactions	8.9%	3.4%
High-value legitimate purchases	7.6%	2.9%
Device or channel change	6.1%	2.5%

G. Discussion

The experimental results confirm the central hypothesis of this work: false positive reduction is fundamentally a representation and data exposure problem. By modeling behavior explicitly and augmenting training data with realistic edge cases, the proposed framework achieves significant precision gains without sacrificing fraud detection effectiveness.

Importantly, the improvements are consistent across models and scenarios, indicating that the approach is not model-specific but structurally beneficial.

V. Novelty and Research Contributions

This paper makes a substantive and multifaceted contribution to the design of modern fraud monitoring systems by explicitly addressing false positive reduction as a core research objective rather than a secondary optimization outcome. While existing literature has largely focused on improving fraud detection accuracy or recall under extreme class imbalance, this work advances the state of the art by demonstrating that false positives predominantly arise from representational and data exposure limitations rather than model insufficiency alone.

The novelty of this work lies in its integrated treatment of behavior modeling, data augmentation, and training strategy, all explicitly aligned toward reducing false positives under realistic operational conditions. The key research contributions are detailed below.

1. Reframing Fraud Detection as a Behavioral Consistency Problem

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A fundamental conceptual novelty of this work is the reframing of fraud detection from a transaction-centric classification task to a behavior-centric consistency evaluation problem. Most existing systems evaluate transactions as isolated events using static or short-term aggregated features. This approach inherently penalizes legitimate behavioral deviations, resulting in elevated false positives.

In contrast, this paper proposes evaluating each transaction relative to a user-specific behavioral baseline that evolves over time. Fraud is interpreted as a violation of behavioral consistency rather than a deviation from population-level norms. This reframing aligns algorithmic decision-making more closely with human fraud analyst reasoning and provides a principled explanation for why behavior-aware systems exhibit lower false positive rates.

This conceptual shift distinguishes the proposed framework from prior work that merely adds temporal features without redefining the underlying detection paradigm.

2. Behavior-Driven Feature Engineering Explicitly Optimized for False Positives

While behavioral features have appeared in prior studies, they are typically introduced to improve overall classification performance rather than to target false positives specifically. This paper introduces a behavior-driven feature engineering strategy in which features are deliberately designed to tolerate legitimate behavioral evolution while penalizing abrupt, incoherent deviations indicative of fraud.

The novelty lies not in using behavioral features per se, but in **how they are constructed and interpreted**. Temporal, monetary, and contextual features are normalized against personalized historical distributions, enabling the model to differentiate rare-but-valid behavior from malicious activity. This design directly addresses a major root cause of false positives rigid feature interpretations that lack behavioral context.

By embedding tolerance to legitimate variability into the feature space itself, the framework reduces reliance on post-hoc threshold tuning or manual overrides.

3. Explicit Modeling of Borderline Legitimate Behavior

A major empirical insight underlying this work is that a large proportion of false positives originate from borderline legitimate transactions cases that are statistically rare but behaviorally valid. Existing fraud detection literature largely overlooks this category, implicitly assuming that legitimate behavior is sufficiently represented in historical data.

This paper is among the first to explicitly recognize borderline legitimate behavior as a distinct modeling challenge and to incorporate it into the training process. By identifying and representing these edge cases, the proposed framework directly addresses a blind spot in current fraud detection systems.

This contribution is particularly important in dynamic environments where legitimate behavior evolves rapidly due to lifestyle changes, globalization, and emerging payment technologies.

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4. Behavior-Constrained Synthetic Data Generation Beyond Fraud Oversampling

Synthetic data generation has been widely applied to fraud detection, primarily to address minority-class imbalance through fraudulent sample oversampling. This paper introduces a novel extension of synthetic data generation that goes beyond fraud augmentation to include **behavior-constrained synthesis of legitimate transactions near the decision boundary**.

The novelty lies in both the **target** and the **constraints** of data generation. Synthetic samples are generated selectively in regions where false positives are most likely to occur, and all samples are validated against behavioral, temporal, and contextual constraints. This approach avoids the distributional distortion and overfitting risks associated with naïve oversampling techniques.

By enriching the training data with realistic edge cases, the framework enables more precise decision boundary learning, which directly translates into reduced false positives.

5. Precision-Oriented Training Aligned with Operational Reality

Another important contribution of this work is the alignment of model training objectives with real-world operational costs. Unlike prior studies that optimize for accuracy or recall in isolation, this framework adopts precision-sensitive and cost-aware training strategies that explicitly penalize false positives.

Threshold calibration is performed using validation data enriched with borderline legitimate samples, ensuring that the deployed model reflects realistic behavioral variability. This operational alignment ensures that improvements observed during evaluation translate effectively into production environments.

This contribution bridges the gap between academic evaluation metrics and real-world fraud monitoring requirements, which is often cited as a limitation of existing research.

6. Empirical Evidence of Significant and Robust False Positive Reduction

Finally, this work provides strong empirical evidence that the proposed approach delivers substantial and consistent false positive reduction across multiple scenarios and model types. Experimental results demonstrate that the integration of behavior-driven features and constrained synthetic data generation reduces false positive rates by more than half relative to baseline systems, while maintaining competitive fraud detection recall.

Importantly, these gains are observed without reliance on complex model architectures, indicating that the improvements stem from better representation and data exposure rather than model complexity. This robustness underscores the generality and scalability of the proposed framework.

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VI. Conclusion and Future Work

This paper addressed one of the most persistent and operationally expensive challenges in modern fraud monitoring systems: the high rate of false positives generated by automated detection models. While prior research has predominantly focused on improving fraud detection accuracy or recall under severe class imbalance, this work demonstrated that false positives originate primarily from inadequate behavioral representation and insufficient exposure to legitimate but rare transaction patterns during training.

To address this issue, the paper proposed a unified framework that combines behavior-driven feature engineering with behavior-constrained synthetic data generation. By modeling transactions as manifestations of user behavior over time rather than isolated events, the proposed approach enables fraud detection systems to distinguish genuine fraudulent anomalies from legitimate behavioral deviations. Behavior-aware features capture temporal regularity, spending consistency, and contextual stability relative to individualized historical baselines, thereby reducing the tendency of models to overreact to rare but valid behavior.

In addition, the paper introduced a targeted synthetic data generation strategy that augments not only fraudulent samples but also borderline legitimate transactions near the decision boundary. This design directly addresses a critical blind spot in existing fraud detection pipelines, where underrepresented legitimate edge cases frequently lead to false alerts. By enforcing behavioral and causal constraints on synthetic samples, the framework ensures realism while improving decision boundary precision.

Extensive experimental evaluation on large-scale, behaviorally realistic transactional data demonstrated that the proposed framework achieves substantial false positive reduction—exceeding 50% relative to baseline systems—while maintaining competitive fraud detection recall and overall discriminative performance. The results confirm that false positive reduction is not merely a threshold calibration problem but a representational and data exposure challenge that can be effectively addressed through behavior-aware modeling.

Beyond quantitative gains, the proposed approach offers practical advantages for real-world deployment. The framework is model-agnostic, compatible with commonly used classifiers, and incurs no additional runtime overhead, as synthetic data generation is confined to offline training. Furthermore, behavior-driven features improve interpretability by aligning machine decisions with human behavioral reasoning, supporting auditability and regulatory compliance.

Future Work

While the proposed framework demonstrates strong performance, several avenues remain for future research. First, real-world fraud environments are characterized by continuous concept drift, where both fraudulent strategies and legitimate user behavior evolve over time. Extending the framework to incorporate adaptive behavioral baselines and online learning mechanisms would further enhance robustness under non-stationary conditions.

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Second, future work may integrate behavior-driven features with graph-based fraud detection techniques that model relationships among users, merchants, and devices. Combining individual behavioral consistency with network-level anomaly detection could improve resilience against coordinated fraud and organized attacks.

Third, privacy-preserving extensions of the proposed framework warrant investigation. Techniques such as federated learning and differentially private synthetic data generation could enable behavior-aware fraud detection without centralized access to sensitive transaction data, addressing regulatory and ethical concerns.

Finally, large-scale deployment studies using real production data would provide deeper insight into operational impact, including customer satisfaction, review workload reduction, and long-term system stability. Such studies would further validate the practical value of behavior-driven false positive reduction in high-throughput financial systems.

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