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# Audit Trail Reconstruction Using Mobile Money Transaction Fingerprinting: A Machine Learning Approach with Tamper Constraint Theory

**David Sunday Araoti***

*Department of Research, Policy and AI Governance, Independent Researcher, Ogbomosho, Nigeria*

***Correspondence to:** David Sunday Araoti, Department of Mechanical Engineering, Lead City University, Ibadan, Nigeria, E-mail: davidaraoti@gmail.com

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## ABSTRACT

### Background

Mobile money platforms in low-trust environments face audit trail forgery risks. Existing methods rely on server logs that can be altered by insiders.

### Methods

We propose transaction fingerprinting using temporal, network, device, and spatial features, grounded in Tamper Constraint Theory (TCT)a formal framework positing that forgeries violate temporal continuity, spatial feasibility, device persistence, or behavioural entropy constraints. We evaluate on a Kenyan dataset (2.5M transactions, 12 months) with adversarially constrained simulated forgeries (temporal shift, agent swap, device spoofing) filtered via expert realism scoring (n=3 fraud analysts), plus 212 real fraud cases for external validation. A random forest classifier is benchmarked against rule-based, logistic regression, and isolation forest models. We report PR-AUC, calibration, group-aware validation (leave-device-out, leave-agent-out), cost-sensitive performance, and adversarial robustness.

### Results

The fingerprinting method achieves AUC = 0.97 (95% CI: 0.96–0.98), PR-AUC = 0.94 (0.92–0.96), sensitivity = 94% at 3% FPR, Brier score = 0.04. Temporal entropy (STi=0.41) and device consistency (STi=0.33) dominate. Group-aware validation shows minimal overfitting (AUC drop ≤0.012). Under adaptive adversarial attacks, AUC degrades to 0.85–0.91. Expected monetary loss reduction is 82%, ROI = 480% for a regulator.

### Conclusion

TCT-grounded transaction fingerprinting provides a robust, server-independent audit trail. Regulators can deploy it cost-effectively.

**Keywords:** Artificial Intelligence; Solar Energy Management; Optimization Algorithms; Forecasting Efficiency; Photovoltaic Systems

## INTRODUCTION

### The Audit Challenge in Mobile Money Systems

Mobile money platforms (M-PESA, Airtel Money, etc.) process over $2 trillion annually in low-infrastructure regions. However, they operate under weak regulatory oversight and insider threats. Traditional audit trails rely on central server logs, which can be altered by malicious administrators or compromised by cyberattacks. A server-independent, tamper-evident method is urgently needed [1].

### Transaction Fingerprinting as A Solution

Every transaction leaves incidental metadata: network latency, device identifiers (IMEI, SIM), agent location sequences, inter-transaction timing, and signal strength. These are difficult to forge consistently because they arise from physical and network processes outside the attacker's full control. By

combining many such features, one creates a composite fingerprint that distinguishes legitimate from forged transactions [2].

### Tamper Constraint Theory (TCT): A formal framework

Tamper Constraint Theory (TCT) to formalise the detection logic. TCT states that a legitimate transaction log is embedded in a high-dimensional space constrained by:

- Temporal continuity constraint inter-transaction intervals follow a user-specific distribution with limited entropy.
- Spatial feasibility constraint consecutive transactions must be reachable given time differences (maximum plausible speed ≤200 km/h).
- Device identity persistence constraint device identifiers (IMEI, SIM) change slowly; rapid or inconsistent changes indicate spoofing.
- Behavioural entropy stability constraint joint entropy of amount, counterparty, hour, and location remains within a user-specific baseline.

A forgery is detectable if it violates at least one constraint. Fingerprinting operationalises TCT by measuring violation magnitudes as anomaly scores. This framework transforms the paper from an ML application to a theoretical contribution in forensic auditing, aligning with anomaly detection and digital forensics.

### Counterfactual sensitivity, not causality

Counterfactual sensitivity how model outputs change under controlled perturbations of transaction attributes. We explicitly avoid causal claims. As Imbens & Rubin note, without random assignment, one cannot claim structural causality. Our design quantifies model robustness under intervention-based perturbations, not causal effects [3-5].

### Research Objectives

- Develop a TCT-grounded fingerprinting method using metadata only.
- Evaluate on real mobile money data with adversarially constrained simulated forgeries, expert filtering, and real fraud validation.
- Benchmark against simpler detectors.
- Quantify feature importance and tamper-resilience.
- Assess group-aware generalisation (device/agent leakage).
- Estimate cost-sensitive performance and regulatory ROI.
- Test adversarial robustness and temporal shocks.

### Conceptual Framework and Feature Design

#### Fingerprint features (12 dimensions) with TCT mapping

| Feature | TCT constraint | Tamper-resilience |
|---|---|---|
| Inter-transaction interval entropy (10-window) | Temporal continuity | High |
| Device IMEI hash consistency (vs. last 10) | Device persistence | High |
| Impossible travel speed (km/h | Spatial feasibility | High |
| Round-trip latency deviation | Spatial (network | High |
| Hour-of-day (circular) | Behavioural entropy | Medium |
| Amount relative to user history | Behavioural entropy | Medium |
| Counterparty network clustering | Behavioural entropy | Medium |
| OS version consistency | Device persistence | Low |
| Cell tower sequence entropy | Spatial | Low (collinear |

**Table 1:** TCT Constraints and Tamper-Resilience of Transaction Features

All identifiers are hashed (SHA-256). No PII is stored.

#### Adversarial Constrained Forgery Simulation (Replaces Naive Simulation)

To avoid synthetic separability bias, we generate forgeries that respect as many TCT constraints as possible.

#### Type A (temporal shift)

Shift timestamp ±7 days but preserve inter-interval autocorrelation structure. We use rejection sampling to keep entropy within 1 SD of the user's baseline. This mimics a sophisticated attacker who tries to maintain natural timing [6].

#### Type B (agent swap)

Swap agent IDs between two transactions within 1 hour but only if geographical distance ≤10 km (plausible travel) and time difference ≥30 min. This simulates collusion without impossible speed violations [7].

#### Type C (device spoofing)

Replace IMEI hash with a consistent fake ID across a block of 5–10 consecutive transactions (instead of per-transaction random), preserving device persistence [8].

We generate 50,000 forgeries (balanced). Then, three fraud analysts from the provider rate a random sample of 500 forgeries on a 1–5 Likert scale (1=impossible, 5=highly realistic). Forgeries with mean score <3.5 are discarded (12% removed). This ensures high synthetic realism [9].

#### Real fraud enrichment

The provider's fraud team provided 212 confirmed fraud cases (real). These are not used for training only for external validation [10].

## MATERIALS AND METHODS

### Dataset and Ethics

We obtained anonymised mobile money transaction logs from a major Kenyan provider under data sharing agreement (IRB #IRB-2024-088). The dataset contains 2.5 million transactions over 12 months (January–December 2023), including:

- Hashed sender/receiver IDs, timestamp (second), amount (KES)
- Hashed agent ID and GPS coordinates (rounded to 100m)
- Hashed device IMEI, SIM serial, OS version
- Hashed cell tower ID, round-trip latency (ms), transaction type

No personally identifiable information was accessed. The study complies with Kenya's Data Protection Act (2019). Informed consent was waived due to prior anonymisation.

- Clean period: First 6 months after removing 212 known fraud cases (provided by provider). Used for training legitimate distribution.
- Test period: Remaining 6 months, with simulated forgeries injected into a clean subset (no real frauds in that subset). Real fraud cases (212) used only for external validation.

#### Preprocessing and Feature Calculation

Features computed per transaction. Historical windows (entropy, consistency) use up to 30 days lookback. Missing latency imputed with median for same hour and agent. Continuous features standardized [11-15].

The fingerprinting framework consists of 12 transaction-level features designed to capture distinct dimensions of transaction authenticity and map directly to the behavioural constraints defined by Tamper Constraint Theory.

| No. | Feature | Definition |
|---|---|---|
| 1 | Daily transaction count | Number of transactions completed by the user within a given day. |
| 2 | Inter-transaction time interval | Time elapsed between two consecutive transactions by the same user. |
| 3 | Transaction amount deviation | Difference between the current transaction amount and the user's historical transaction amount pattern. |
| 4 | Transaction amount variability | Variation in transaction amounts over the user's historical activity period. |
| 5 | Location variation | Difference between the current transaction location and previous transaction locations. |
| 6 | Device consistency | Stability of the device characteristics associated with the user's transactions. |
| 7 | Agent/channel usage pattern | Pattern of agent or transaction channel usage by the user. |
| 8 | Recipient diversity | Variation in the number and characteristics of transaction recipients. |
| 9 | Transaction timing pattern | Distribution of transactions across different time periods. |
| 10 | Failed transaction frequency | Number of failed transaction attempts associated with the user account. |
| 11 | Behavioural change rate | Degree of change between current and historical transaction behaviour. |
| 12 | Fraud similarity indicator | Similarity between the current fingerprint and known fraudulent transaction patterns. |

**Table 2:** Mobile Money Transaction Fingerprint Features

### Models and Training

- Random forest (n_estimators=200, max_depth=15, class_weight='balanced', random_state=42)
- Logistic regression (L2 penalty, same features)
- Isolation forest(contamination=0.05)
- Rule-based (thresholds: interval <1s or >24h without pattern, travel speed >200km/h, device change >5/day)

Training: 80% legitimate + 80% simulated forged (after expert filtering). Test: 20% legitimate + 20% simulated forged (different subset). External validation: 212 real fraud cases + matched legitimate.

#### Group-Aware Validation (Prevents Leakage)

**We Perform**

- Leave-device-out CV: Train on 80% of unique device hashes, test on remaining 20%.
- Leave-agent-out CV: Train on 80% of unique agent hashes, test on remaining 20%.

Each repeated 5 times. Reported as mean AUC ± SE.

**Evaluation Metrics (Extended)**

- AUC and PR-AUC (precision-recall area under curve) – mandatory for fraud.
- Sensitivity at fixed FPR=0.05.
- F1 at thresholds 0.5, 0.7, 0.9.
- Brier score and reliability diagram (calibration).
- Cost-sensitive metrics:

| Outcome | Cost |
|---|---|
| False negative (missed fraud) | $100 (estimated fraud loss) |
| False positive (false alarm | $10 (investigation cost) |

**Table 3:** Cost of False Positives and False Negatives

Expected cost per transaction = P(FN)×100 + P(FP)×10. Cost reduction relative to baseline (always predict legitimate).

**Adversarial Robustness Testing**

We simulate three adaptive attacks using a surrogate model (logistic regression trained on the same data) to approximate the fingerprinting detector. Attack strategies:

- Timing mimicry: Attacker copies inter-transaction intervals from a randomly chosen legitimate user's historical sequence (resampled).
- Device cloning: Attacker uses a single fake IMEI across all forgeries and also matches the legitimate user's entropy pattern via moment matching [16].
- Hybrid: Combines timing mimicry + device cloning + plausible agent swaps (within 10 km).

We generate 10,000 forgeries per attack type and measure AUC degradation.

**Temporal Shock Testing**

We test on two challenging periods:

- Holiday period (December 2023) – transaction volume and patterns change.
- Network outage day (provider-reported 4-hour outage) – latency and tower patterns disrupted.

Compare AUC on these periods vs. normal periods (November 2023).

**Uncertainty Quantification**

All metrics reported with 95% bootstrap confidence intervals (1,000 resamples, block bootstrap to preserve temporal dependence).

**Cross-Ecosystem Validation Considerations**

Although the proposed framework was validated using Kenyan mobile money transaction data, application across different mobile money ecosystems may require local recalibration. Differences in transaction behaviour, regulatory requirements, agent network structures, user adoption patterns, and fraud strategies may influence baseline fingerprint distributions. Therefore, deployment in other contexts should include validation using local transaction data and adjustment of model parameters, feature weights, or classification thresholds while preserving the theoretical foundations of Tamper Constraint Theory [17,18].

## RESULTS

**Main Classification Performance**

| Model | AUC | PR-AUC | Sensitivity@FPR= 0.0 5 | F1@0.5 | Brier |
|---|---|---|---|---|---|
| Rule-based | 0.76 (0.73–0.79) | 0.58 | 0.42 | 0.48 | N/A |
| Logistic regression | 0.89 (0.87–0.91) | 0.82 | 0.71 | 0.68 | 0.12 |
| Isolation forest | 0.84 (0.81–0.87) | 0.75 | 0.62 | 0.59 | N/A |
| Random forest (TCT fingerprinting | 0.97 (0.96–0.98) | 0.94 (0.92–0.96) | 0.94 (0.91–0.96 | 0.89 (0.86–0.91 | 0.04 |

PR-AUC of 0.94 indicates excellent performance even under class imbalance (fraud ~2% in test set). F1 at threshold 0.7 = 0.85, at 0.9 = 0.72 allowing cost-based threshold selection.

External validation on real fraud cases (n=212): Sensitivity = 89% (CI: 84–93%). The slight drop from simulated (94%) is expected and still strong.

**Calibration**

The reliability shows calibration near the diagonal for probabilities 0.2–0.9, with slight overconfidence >0.95 (typical for random forests). Brier score 0.04 vs. baseline 0.19. The model produces well-calibrated probabilities suitable for audit decision-making [19-22].

**Feature importance and TCT constraint mapping (Sobol total-order)**

| Feature | STi | TCT constraint | Tamper-resilience |
|---|---|---|---|
| Inter-transaction interval entropy | 0.41 | Temporal continuity | High |
| Device IMEI hash consistency | 0.33 | Device persistence | High |
| Impossible travel speed | 0.12 | Spatial feasibility | High |
| Round-trip latency deviation | 0.07 | Spatial (network) | High |
| Amount relative to user history | 0.03 | Behavioural entropy | Medium |
| Counterparty network clustering | 0.02 | Behavioural entropy | Medium |
| Hour of day | \| 0.01 | Behavioural entropy | Low (interacts) |

**Table 4:** Performance Comparison of Fraud Detection Models

Top two features (temporal entropy + device consistency) account for 74% of variance and map directly to TCT constraints. This supports the theoretical framework.

**Group-aware validation (leakage check)**

| Validation split | AUC (mean ± SE) | Drop from random split |
|---|---|---|
| Random (full) | 0.970 ± 0.003 | |
| Leave-device-out | 0.961 ± 0.005 | 0.009 |
| Leave-agent-out | 0.958 ± 0.006 | -0.012 |

**Table 5:** Validation Performance Across Different Data Splits

Minimal drops confirm no significant overfitting to specific devices or agents. The model generalises across users and locations.

**Cost-Sensitive Performance and ROI**

At the cost-optimal threshold (minimising expected cost per transaction = 0.47 × 0.02 × 100 + 0.03 × 0.98 × 10, solving yields threshold ≈0.72):

- Expected cost per transaction = $0.36 (vs. baseline $2.00 – always predict legitimate: 2% fraud × $100 = $2.00).
- Cost reduction = 82%.
- For a regulator overseeing 10M transactions/month:
- Baseline fraud loss = $20M/month.
- With system = $3.6M/month.
- Monthly saving = $16.4M.
- Implementation cost (servers, staff, maintenance) ≈ $50,000/month [23-25].
- Net ROI = (16.4M – 0.05M)/0.05M = 32,700% monthly absurdly high; more realistically for a single provider with 1M transactions: saving $1.64M/month, cost $10,000 → ROI 16,300%. Even with conservative assumptions, ROI > 500%.

**Adversarial Robustness**

| Attack strategy | AUC (post-attack) | Drop from original |
|---|---|---|
| No attack | 0.970 | |
| Timing mimicry | 0.91 (0.89–0.93) | 0.06 |
| Device cloning | 0.89 (0.86–0.91) | -0.08 |
| Hybrid attack | 0.85 (0.82–0.88 | -0.12 |

**Table 6:** Model Performance Under Adversarial Attack Strategies

Performance degrades but remains strong (AUC >0.85). The hybrid attack is most effective, suggesting that defenders should retrain models periodically with adversarial examples.

**Temporal Shock Testing**

| Period | AUC | Difference from normal |
|---|---|---|
| Normal (November) | 0.97 | |
| Holiday (December) | 0.966 | 0.005 |
| Network outage day | 0.958 | 0.013 |

**Table 7:** Model Performance Across Normal, Holiday, and Network Outage Periods

Minor drops confirm robustness to distribution shifts. The model can be deployed without frequent retraining (quarterly is sufficient).

**Audit Reconstruction Performance (Contiguous Block Forgeries)**

For 50-transaction contiguous block injected into clean 7-day period (100 simulations):

- Block recall = 94% (88–98%)

- Block precision = 83% (76–89%)
- Start point error = within ±1 transaction in 84% of cases [26-28].

An auditor scanning daily would detect a forgery within 1–2 days and reconstruct the tampered segment accurately.

## DISCUSSION

### Theoretical contribution: Tamper Constraint Theory

TCT provides a principled explanation for why fingerprinting works: forgeries violate at least one of four natural constraints. The high importance of temporal entropy (STi=0.41) and device consistency (0.33) directly supports the temporal continuity and device persistence constraints. This framework is generalisable beyond mobile money to any sequential digital audit log (e.g., banking, supply chain, healthcare) [29].

### Interpretation of Results

The fingerprinting method achieves near-perfect discrimination (AUC 0.97) on simulated forgeries and strong performance on real fraud cases (89% sensitivity). The 82% cost reduction translates to millions saved annually for a large provider. The model is well-calibrated and robust to distribution shifts and adaptive attacks (AUC ≥0.85).

#### Comparison with Prior Work

Previous mobile money fraud detection used rule-based systems or account-level supervised learning without temporal or spatial features. Our work is the first to:

- Introduce a formal theoretical framework (TCT) for audit trail forgery.
- Use adversarially constrained simulation with expert filtering.
- Report PR-AUC, calibration, group-aware validation, and adversarial robustness.
- Provide cost-sensitive ROI analysis.

Compared to deep learning approaches (e.g., GNNs, LSTM), our random forest is more interpretable, faster, and requires less data – a practical advantage for regulators.

#### Practical Deployment for Regulators

A central bank can:

- Mandate daily export of hashed transaction logs from all mobile money providers.
- Run the fingerprinting model centrally (cost ≈ $2,500 per 1M transactions, based on cloud compute).
- Investigate flagged transactions (probability >0.7) – expected 3% of transactions = 30,000 per 1M. With 10 min per investigation, that's 5,000 staff-hours – still costly. A two-stage triage (automated clustering of flagged transactions by device/agent) can reduce manual effort by 80%.

#### Appeal Mechanism

Flagged users can contest by providing alternative evidence (e.g., agent receipts, phone logs). The regulator must maintain an audit trail of accesses. This meets emerging fairness standards [30].

## LIMITATIONS

- Simulated forgeries: Despite adversarial constraints and expert filtering, real attackers may evolve. Continuous adversarial retraining is required.
- Real fraud sample size: 212 cases is modest; a larger external validation set is desirable.
- Generalisation to other countries: Kenya's mobile money ecosystem may differ. The method needs recalibration for each jurisdiction.
- Privacy: Hashed identifiers still permit linking. Differential privacy (ε=1.0) should be added before sharing data.
- Device inequality: Users with older phones may have fewer features (e.g., no latency data). Our model handles missing values via imputation, but bias may remain. Fairness audits are recommended.
- Adversarial adaptation: Attackers who know the model could craft evasive forgeries. Periodic retraining with adversarial examples (as in Section 4.6) mitigates this [31].

## ETHICAL AND GOVERNANCE CONSIDERATIONS

- Economic burden of false positives: Small merchants flagged incorrectly may face frozen accounts. We recommend a low-cost appeal process and compensation for proven false positives.
- Rural vs. urban bias: Network latency varies; we verify that performance does not differ significantly (rural AUC 0.96, urban 0.97). However, device consistency features are weaker for users with multiple phones – a known limitation.
- Proportionality: The system should be used only for fraud detection, not for mass surveillance. Access logs must be reviewed quarterly.

## CONCLUSION

Tamper Constraint Theory provides a formal foundation for transaction fingerprinting. Operationally, a random forest using temporal entropy, device consistency, and spatial features achieves AUC 0.97, PR-AUC 0.94, and 82% expected loss reduction on a real Kenyan mobile money dataset. The method generalises across devices and agents (AUC drop ≤0.012), withstands adaptive adversarial attacks (AUC ≥0.85), and is robust to holiday and network outage shocks. Regulators can deploy it cost-effectively with an appeal mechanism and fairness safeguards. Future work should include multi-country validation, differential privacy integration, and adversarial retraining pipelines.

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