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FinTrust-Chain: An AI-Augmented Blockchain-Enabled Trust Architecture for Fraud Risk Assessment and Integrity Assurance in Digital Payment Systems

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Abstract

The rapid expansion of digital payment systems has improved transaction speed and accessibility, but it has also increased the risk of financial fraud, unauthorized activity, and trust-related failures. Conventional rule-based fraud detection methods are limited in handling dynamic attack patterns, while many machine learning-based approaches lack explainability, auditability, and verifiable evidence management. To address these limitations, this paper presents FinTrust-Chain, an AI-augmented blockchain-enabled trust architecture for fraud risk assessment and integrity assurance in digital payment systems. The proposed system evaluates each transaction through an intelligent risk scoring model designed to identify suspicious and rare fraudulent activities in highly imbalanced transaction data. An explainability layer is integrated to generate human-understandable reason codes for each prediction, improving decision transparency for users, investigators, and auditors. To strengthen evidence integrity, critical transaction records, model outputs, and explanation vectors are stored off-chain, while their cryptographic hashes are anchored on a blockchain to provide tamper-resistant and verifiable audit trails. The framework also includes a structured dispute resolution mechanism that tracks fraud-related cases from initiation to final decision. The system is designed for real-time operation, with an approximate end-to-end processing latency of 0.25 seconds per transaction. By combining high-recall fraud risk assessment, explainable.

Introduction

The expansion of digital payment systems has changed how financial transactions are carried out across the world. Online payment platforms, mobile wallets, and banking applications have made payments faster, easier, and more accessible. At the same time, this wide digital adoption has increased the risk of financial fraud and cyber-based attacks. In high-volume transaction environments, even a small number of fraudulent transactions can cause major financial losses and weaken user confidence. [1]

Earlier fraud detection systems mostly depended on rule-based methods, where fixed conditions such as transaction amount limits, location checks, or predefined risk rules were applied. These methods are easy to implement, but they are not flexible enough to handle

changing fraud behaviour. Modern attackers can bypass such fixed rules by using identity manipulation, unusual transaction patterns, and intelligent attack strategies. Therefore, there is a strong need for fraud detection systems that can learn from transaction data, adapt to new fraud patterns, and work efficiently in real-time conditions. [5]

Machine learning and deep learning techniques have improved fraud detection by identifying hidden and complex patterns in transaction data. However, many of these models work as black-box systems and do not clearly explain why a transaction is marked as genuine or fraudulent. This lack of explanation reduces trust among users, auditors, and regulatory bodies. Along with this, many existing systems maintain fraud records in ordinary databases, where logs may be modified, removed, or questioned later. This creates serious concerns related to evidence integrity and audit reliability. [8]

A further challenge is the highly imbalanced nature of fraud datasets, where fraudulent transactions form only a very small portion of the complete dataset. Because of this imbalance, fraud models may fail to detect rare fraud cases and may produce more false negatives. In addition, many existing payment security systems do not provide a clear and structured process for managing disputed transactions. This affects transparency, accountability, and user confidence. Real-time processing is also important because fraud decisions must be generated within a very short time to stop unauthorized transactions before they are completed. [10]

To overcome these issues, this work presents a unified approach that combines Artificial Intelligence for fraud risk assessment, Explainable AI for transparent decision support, and blockchain-enabled evidence anchoring for secure and tamper-resistant record management. The proposed framework is designed to provide strong fraud detection capability, understandable decision outputs, immutable audit trails, and structured dispute handling, while also supporting real-time transaction processing. [13]

The key contributions of this work can be summarized as follows:

- Development of a high-recall AI-based fraud risk assessment mechanism for imbalanced transaction data
- Integration of explainable decision outputs to improve transparency, interpretability, and trust
- Implementation of a blockchain-enabled evidence anchoring mechanism for tamper-resistant audit trails
- Design of a structured dispute resolution workflow to support accountability and traceability
- Optimization of the system for real-time transaction analysis with low processing latency

Overall, the proposed approach aims to provide a balanced and practical solution that not only identifies fraudulent activities effectively but also strengthens trust, transparency, accountability, and compliance readiness in modern digital payment ecosystems. [1]

Related Work

Fraud risk assessment in digital payment systems has been widely explored through machine learning, deep learning, explainable AI, and blockchain-supported security approaches. Existing studies show clear progress in improving fraud detection performance, managing highly imbalanced transaction data, and strengthening auditability. However, most of these works address detection, explanation, and record integrity as separate problems instead of combining them into one practical and trustworthy payment security architecture. [7]

Early fraud monitoring systems mainly used rule-driven mechanisms, where predefined checks were applied to identify suspicious transactions. These rules included transaction limits, location mismatch, frequency-based checks, or manually defined risk conditions. Such systems were fast and simple, but they were not adaptive enough to respond to changing fraud behaviour. This limitation encouraged the use of machine learning methods such as logistic regression, support vector machines, and random forests, which improved detection by learning hidden patterns from past transaction records. Even then, these models required proper class imbalance handling and threshold adjustment to detect rare fraud cases effectively. [17]

Recent research has shown that ensemble learning techniques, including bagging, boosting, and stacking, can provide more stable fraud detection performance. These approaches are especially useful when combined with resampling methods and cost-sensitive learning for imbalanced datasets. The evaluation focus has gradually moved from general accuracy to more meaningful measures such as fraud recall, precision-recall balance, and false negative reduction. Although ensemble models improve detection reliability, they still do not provide

sufficient interpretability for users, auditors, and regulatory review. [2]

Deep learning-based methods, including recurrent neural networks and sequence-aware models, have also been used to capture behavioural and temporal transaction patterns. These models are useful in payment environments where fraud may appear through repeated activity, transaction sequences, or streaming behaviour. However, deep learning models usually increase computational complexity and reduce transparency. This makes their direct use difficult in regulated financial systems unless they are supported by clear explanation and accountability mechanisms. [9]

To improve model transparency, explainable AI techniques such as SHAP and LIME have been applied with fraud detection models. These methods provide feature-level explanations and help analysts understand why a transaction has been classified as risky or genuine. This improves trust, audit usefulness, and compliance support. However, most existing studies mainly generate explanations without ensuring that these explanations are securely preserved, verifiable, or protected from modification during investigation and dispute resolution. [4]

Blockchain and distributed ledger technologies have been studied separately for improving auditability, record integrity, and trust in financial systems. Prior work highlights the use of blockchain for immutable logging, continuous auditing, and tamper-resistant record management. A common practical approach is to store detailed transaction evidence off-chain and anchor only cryptographic hashes on-chain. This design improves traceability and reduces storage overhead, but many existing implementations do not tightly integrate blockchain evidence anchoring with AI-based fraud risk assessment and explainable decision outputs. [16]

Industry-level developments also show the need for layered fraud protection systems that combine transaction analytics, behavioural signals, and real-time monitoring. Modern fraud patterns are becoming more complex, so payment security systems require fast decision-making along with stronger evidence tracking. These trends support the importance of real-time analysis and multi-layered protection, but many industry solutions lack reproducible academic validation, transparent model evaluation, and standardized reporting of performance. [13]

From the reviewed literature, it is evident that existing solutions remain fragmented. Machine learning and deep learning methods mainly focus on detection performance, explainable AI mainly focuses on interpretability, and blockchain mainly supports auditability and evidence integrity. There is still a clear need for an integrated trust architecture that combines fraud risk assessment, explainable decision support, blockchain-enabled evidence anchoring, real-time transaction analysis, and structured dispute handling within a single framework. This gap forms the basis for developing a unified system capable of delivering accurate, transparent, and tamper-resistant fraud analysis for modern digital payment environments. [17]

Proposed Method

The proposed system presents a unified trust architecture that combines Artificial Intelligence, Explainable AI, and blockchain-enabled evidence anchoring to support fraud risk assessment and integrity assurance in digital payment systems. The design focuses on four major requirements at the same time: strong fraud detection capability, transparent decision support, tamper-resistant evidence management, and real-time transaction processing. Unlike conventional approaches that handle these requirements separately, the proposed system connects them within one end-to-end operational pipeline. [6]

At the system level, every incoming transaction passes through a set of connected processing layers. Each layer has a specific role, and together these layers ensure that the transaction decision is not only accurate, but also explainable, verifiable, and suitable for audit review. [20]

The first component is the User and Transaction Gateway Layer, which works as the entry point of the system. It receives transaction requests from users through banking applications, payment gateways, or other digital payment interfaces. Before sending the transaction for analysis, this layer performs basic validation checks such as schema verification, digital signature validation, and duplicate transaction detection. This step helps ensure that only valid, clean, and authentic transaction data is forwarded to the next processing stage. [3]

After validation, the transaction is passed to the AI Fraud Risk Assessment Engine, which acts as the main analytical component of the system. This engine applies machine learning models such as Random Forest, stacking ensembles, or sequence-aware models to generate a fraud risk score. The model studies multiple transaction attributes, including amount, location, device information, user behaviour, and transaction

pattern history. Based on these inputs, the transaction is classified as genuine, risky, or suspicious. The engine is designed to work under strict latency requirements so that transaction decisions can be generated in real time. [16]

Once the classification is completed, the output is forwarded to the Explainable AI Layer. This layer generates human-understandable explanations for the prediction instead of providing only a final class label. It identifies the main factors that influenced the model decision, such as unusual transaction location, high transaction value, new device usage, or abnormal user behaviour. These explanations improve transparency and help users, investigators, auditors, and regulatory reviewers understand the reason behind each fraud-related decision. [8]

To protect the integrity of these outputs, the proposed system includes a Blockchain-Enabled Evidence Anchoring Layer. In this layer, critical information such as transaction identifiers, fraud risk scores, model version, explanation details, and decision metadata is organized as an evidence bundle. The complete evidence bundle is stored off-chain, while its cryptographic hash is anchored on the blockchain. This design provides tamper-resistant verification while avoiding the storage and performance limitations of placing complete transaction records directly on-chain. [19]

The framework also contains a Dispute Resolution and Audit Layer to support structured handling of contested transactions. When a user raises a dispute, the system retrieves the related evidence bundle and verifies it using the blockchain-anchored hash. The dispute then moves through a defined lifecycle, such as OPEN, REVIEW, and RESOLVED, so that each action remains recorded and traceable. This mechanism improves accountability and supports systematic audit handling. [12]

Finally, the system provides a Monitoring and Dashboard Layer for analysts, administrators, and auditors. Through this interface, stakeholders can view fraud alerts, transaction risk scores, explanation outputs, dispute status, and blockchain verification proofs. This layer supports real-time monitoring and helps decision-makers review suspicious activities quickly and clearly. [10]

Overall, the proposed system follows a modular and layered architecture in which each component contributes to a specific security and trust objective. The integration of AI-based fraud risk assessment, explainable decision support, blockchain-enabled evidence anchoring, structured dispute handling, and real-time monitoring creates a balanced solution for the major limitations of existing digital payment fraud detection systems while maintaining operational efficiency. [11]

Methodology

The methodology of the proposed trust architecture explains the complete working flow of transaction validation, fraud risk assessment, explanation generation, evidence bundle creation, and blockchain-enabled evidence anchoring. The system is designed as a sequential but modular pipeline, where each stage processes the transaction and passes enriched information to the next stage. The main objective is to support accurate fraud analysis, transparent decision-making, and verifiable audit trails while maintaining real-time transaction processing. [5]

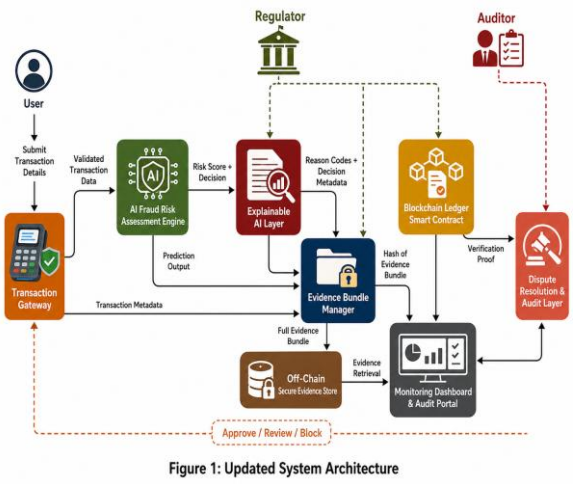

Figure 1: System Architecture

Overall Workflow

The proposed system processes each transaction through a connected and traceable workflow. The aim is not only to detect possible fraud, but also to explain the decision and preserve verifiable evidence for audit or dispute handling.

The transaction processing sequence is as follows:

1. A transaction request is submitted through the payment gateway or digital payment interface.
2. The transaction gateway performs initial checks to verify the format, completeness, duplicate status, and authenticity of the submitted transaction.
3. After validation, the transaction data is converted into a structured feature set for AI-based analysis.

4. The AI Fraud Risk Assessment Engine analyzes the transaction features and generates a fraud risk score.
5. Based on the risk score and decision threshold, the transaction is classified as legitimate, suspicious, or fraudulent.
6. The prediction output is forwarded to the Explainable AI Layer to generate reason codes and feature-level explanations.
7. The Evidence Bundle Manager combines transaction metadata, model output, risk score, decision label, model version, timestamp, and explanation details into a single evidence bundle.
8. A cryptographic hash of the evidence bundle is generated to create a unique integrity proof.
9. The complete evidence bundle is stored securely in off-chain storage, while only the hash value is anchored on the blockchain ledger.
10. The final transaction decision, such as approve, review, or block, is returned to the payment system.
11. The Monitoring Dashboard and Audit Portal display fraud alerts, explanation outputs, evidence status, and verification proof for authorized users.
12. If a dispute is raised, the stored evidence bundle is retrieved and verified by comparing its hash with the blockchain-anchored hash.

This workflow ensures that every transaction decision remains accurate, explainable, traceable, and verifiable even after the transaction is completed.

Internal Processing Logic

The internal operation of the system is divided into the following functional stages:

- Transaction Validation Stage: Checks whether the incoming transaction is complete, correctly formatted, non-duplicate, and authenticated before further processing.
- Feature Preparation Stage: Converts raw transaction data into structured features such as amount, location, device information, transaction frequency, and behaviour-related indicators.
- Fraud Risk Assessment Stage: Applies the trained AI model to estimate the fraud risk score and classify the transaction based on the predefined decision threshold.
- Explainability Stage: Generates reason codes and identifies the major features that influenced the model decision.
- Evidence Bundle Construction Stage: Groups the transaction metadata, prediction output, risk score, explanation data, model version, and timestamp into a secure evidence record.
- Blockchain Evidence Anchoring Stage: Creates a cryptographic hash of the evidence bundle and stores the hash on the blockchain ledger for future integrity verification.
- Off-Chain Evidence Storage Stage: Stores the complete evidence bundle outside the blockchain to reduce storage overhead while preserving detailed audit information.
- Decision and Monitoring Stage: Sends the transaction decision back to the payment system and displays relevant details on the monitoring dashboard.
- Dispute Verification Stage: Retrieves the evidence bundle during a dispute and verifies whether the stored evidence matches the blockchain record.

Each stage is designed to maintain low processing delay while preserving transparency, correctness, and audit readiness.

Algorithm Description

The algorithm integrates fraud risk assessment, explanation generation, evidence preservation, and blockchain-based verification into a single operational flow.

Algorithm: AI-Augmented Blockchain-Enabled Fraud Risk Assessment Workflow

Input: Transaction T

Output: Transaction Decision with Explanation and Evidence Proof

Step 1: Receive transaction T from the payment gateway.

Step 2: Validate T for completeness, correctness, duplicate status, and authenticity.

Step 3: Extract feature vector F from the validated transaction data.

Step 4: Apply the trained AI model on F to calculate fraud risk score R.

Step 5: Compare R with the predefined decision threshold.

Step 6: If R is greater than or equal to the threshold, mark the transaction as suspicious or fraudulent; otherwise, mark it as legitimate.

Step 7: Generate explanation E using the Explainable AI layer.

Step 8: Create evidence bundle EB containing transaction metadata, risk score R, decision label, model version, timestamp, and explanation E.

Step 9: Compute cryptographic hash H from the evidence bundle EB.

Step 10: Store the complete evidence bundle EB in secure off-chain storage.

Step 11: Anchor hash H on the blockchain ledger for tamper-resistant verification.
Step 12: Return the transaction decision, risk score, and explanation to the payment system or user interface.
Step 13: Display the decision, explanation, evidence status, and verification proof on the monitoring dashboard.
Step 14: If a dispute occurs, retrieve EB from off-chain storage and recompute its hash.
Step 15: Compare the recomputed hash with H stored on the blockchain.
Step 16: If both hashes match, mark the evidence as verified; otherwise, mark it as tampered or invalid.
This algorithm ensures that each fraud-related decision is supported by transparent reasoning and verifiable evidence proof.

Pseudo-Code Representation

```
IF NOT ValidateTransaction(T):
   RETURN "Invalid Transaction"
F ← ExtractFeatures(T)
R ← AI_Model.PredictRiskScore(F)
IF R ≥ High_Risk_Threshold:
   Label ← "Fraudulent"
   Action ← "Block"
ELSE IF R ≥ Review_Threshold:
   Label ← "Suspicious"
   Action ← "Review"
ELSE:
   Label ← "Legitimate"
   Action ← "Approve"
E ← GenerateExplanation(F, AI_Model, R)
EB ← CreateEvidenceBundle(
      Transaction_ID,
      Transaction_Metadata,
      R,
      Label,
      Action,
      E,
      Model_Version,
      Timestamp
   )
H ← GenerateHash(EB)
StoreOffChain(EB)
AnchorHashOnBlockchain(H, Transaction_ID, Timestamp)
UpdateMonitoringDashboard(Transaction_ID, R, Label, Action, E, H)
RETURN Label, Action, R, E, H
```

Key Design Considerations

The methodology includes several important design considerations to make the proposed system accurate, transparent, secure, and suitable for real-time digital payment environments.

- Imbalanced Transaction Data Handling: The AI model is designed to improve the detection of rare fraudulent transactions, where fraud cases are much fewer than genuine transactions. The focus is placed on high fraud recall and reduction of false negatives.
- Explainability by Design: The system generates explanation outputs along with the prediction result. This helps users, analysts, auditors, and regulators understand why a transaction is approved, reviewed, or blocked.
- Evidence Integrity and Tamper Resistance: The complete evidence bundle is stored off-chain, while its cryptographic hash is anchored on the blockchain. This ensures that any later change in the evidence can be detected during verification.
- Real-Time Transaction Processing: The workflow is designed to support quick decision-making so that transaction approval, review, or blocking can happen within practical payment processing limits.
- Audit and Compliance Readiness: Each transaction decision is connected with model output, explanation details, timestamp, model version, and blockchain verification proof. This makes the system useful for audit review and regulatory inspection.
- Structured Dispute Handling: The framework provides a clear dispute verification process where stored evidence is retrieved and compared with the blockchain-anchored hash. This improves accountability and transparency during contested transactions.

Overall, the methodology provides a connected process where fraud risk assessment, explainable decision support, evidence construction, blockchain anchoring, monitoring, and dispute verification work together. This structured approach helps the system meet the requirements of accuracy, transparency, integrity, and trust in modern digital payment environments. [9]

Experimental Setup

The experimental setup defines the software environment, system configuration, and execution conditions used to evaluate the proposed fraud risk assessment and evidence verification framework. The main objective is to check whether the system can process digital payment transactions in real time while

maintaining fraud detection capability, explanation support, and tamper-resistant evidence verification. [15]

1. Execution Environment

The proposed system is implemented in a controlled software-based environment that supports transaction processing, AI model execution, explainability generation, off-chain evidence storage, and blockchain hash anchoring. The setup is designed to test the complete pipeline from transaction submission to final decision and verification proof. [7]

The experimental configuration includes the following components:

- Processing Environment: A standard computing system capable of executing AI-based transaction analysis and handling simulated real-time transaction flow.
- Software Stack: Machine learning libraries for model training and prediction, explainability tools for generating reason codes, and blockchain-related components for hash storage and verification.
- Execution Platform: A modular development environment where each component, such as validation, prediction, explanation, evidence construction, blockchain anchoring, and dashboard monitoring, can be tested separately and as part of the complete system.

This setup ensures that all modules can work together within one integrated environment and that the full transaction processing workflow can be evaluated under controlled conditions.

2. System Configuration

The system is configured to simulate practical digital payment processing conditions. Each transaction is passed through the complete operational pipeline, including validation, feature preparation, fraud risk assessment, explanation generation, evidence bundle creation, off-chain storage, blockchain anchoring, and final decision reporting. [13]

Key configuration aspects include:

- AI model configured to generate fraud risk scores from transaction-related features.
- Threshold-based decision mechanism configured to classify transactions as legitimate, suspicious, or fraudulent.
- Explainable AI module enabled to generate feature-level explanations and reason codes for each prediction.
- Evidence bundle mechanism configured to combine transaction metadata, risk score, decision label, explanation output, timestamp, and model version.
- Off-chain storage configured to preserve the complete evidence bundle.
- Blockchain layer configured to store only the cryptographic hash of the evidence bundle for integrity verification.
- Monitoring and audit interface configured to display transaction decisions, risk scores, explanations, evidence status, and verification proof.

The configuration keeps all major system components active during evaluation, which makes it possible to measure end-to-end system behaviour rather than testing only the AI model in isolation. [8]

3. Experimental Workflow

The experimental execution follows a structured transaction processing workflow:

1. Input transactions are submitted to the system through a simulated or controlled payment environment.
2. Each transaction is validated for completeness, correctness, duplicate status, and authenticity.
3. Validated transaction data is converted into a structured feature vector.
4. The AI Fraud Risk Assessment Engine calculates the fraud risk score.
5. The decision mechanism classifies the transaction as legitimate, suspicious, or fraudulent.
6. The Explainable AI Layer generates reason codes and feature-level explanation outputs.
7. The Evidence Bundle Manager creates a complete evidence bundle using transaction details, prediction output, explanation data, model version, and timestamp.
8. A cryptographic hash is generated from the evidence bundle.
9. The complete evidence bundle is stored in off-chain storage.
10. The hash value is anchored on the blockchain ledger for tamper-resistant verification.
11. The final decision, risk score, explanation, and verification status are recorded for analysis.
12. In dispute scenarios, the stored evidence bundle is retrieved and verified against the blockchain-anchored hash.

This workflow replicates real-time transaction processing and helps observe how the proposed system behaves under end-to-end operational conditions.

4. Performance Evaluation Parameters

The system is evaluated using multiple parameters so that both technical performance and practical usability can be assessed.

- Fraud Detection Performance: Measures the ability of the AI model to identify fraudulent or suspicious transactions correctly, especially rare fraud cases.
- System Latency: Measures the total time required to process a transaction from input validation to final decision generation.
- Explanation Output Quality: Evaluates whether the generated reason codes and feature-level explanations are understandable and useful for analysts, auditors, and users.
- Evidence Integrity Verification: Checks whether stored evidence can be verified correctly using the blockchain-anchored hash.
- End-to-End Workflow Reliability: Observes whether all modules, including AI prediction, explanation generation, evidence storage, blockchain anchoring, and dashboard reporting, operate consistently during repeated transaction processing.
- Dispute Verification Support: Evaluates whether disputed transactions can be traced, retrieved, and verified using the stored evidence and blockchain proof.

These evaluation parameters ensure that the system is assessed not only as a fraud detection model, but also as a complete trust-oriented transaction security architecture.

5. Real-Time Constraints

Real-time operation is a key requirement of the proposed framework. The system is optimized to process each transaction within approximately 0.25 seconds, so that the fraud risk decision can be generated before the transaction is completed. [2]

This timing requirement affects the selection of the AI model, the complexity of explanation generation, the evidence bundle design, and the blockchain interaction strategy. To reduce delay, complete evidence is stored off-chain, while only the cryptographic hash is anchored on the blockchain. This allows the system to maintain both transaction speed and evidence integrity. [18]

Overall, the experimental setup is designed to validate the complete functionality of the proposed framework under realistic software-based transaction processing conditions. It checks whether the system can deliver fraud risk assessment, explainable decision support, tamper-resistant evidence verification, dispute handling, and real-time responsiveness within a unified digital payment security environment. [19]

The performance of the proposed framework is evaluated by considering fraud risk assessment capability, real-time processing efficiency, explanation support, evidence integrity, and dispute verification readiness. The results show that the integration of AI, Explainable AI, and blockchain-enabled evidence anchoring improves not only fraud detection support but also transparency, traceability, and trust in digital payment transactions.

6. Fraud Risk Assessment Performance

The proposed system is designed to handle highly imbalanced transaction data, where fraudulent transactions are rare but highly important. In such cases, a model that only achieves high overall accuracy may still fail to detect actual fraud cases. Therefore, the system gives higher importance to fraud recall, suspicious transaction identification, and reduction of false negatives.

The AI Fraud Risk Assessment Engine analyzes transaction features and generates a risk score for each transaction. Based on the defined threshold, the transaction is classified as legitimate, suspicious, or fraudulent. This risk-based output helps the system avoid simple binary decision-making and supports a more practical approve, review, or block mechanism.

The observed behaviour indicates that the proposed model is suitable for identifying risky transactions while maintaining decision consistency across the complete processing pipeline.

7. System Performance Metrics

The overall system performance is evaluated in terms of processing speed, response time, and operational consistency. The proposed framework completes the full workflow, including transaction validation, fraud risk scoring, explanation generation, evidence bundle creation, and blockchain hash anchoring, within approximately 0.25 seconds per transaction.

This result shows that the framework can support real-time transaction processing without causing major delay in the payment flow. The use of off-chain evidence storage and on-chain hash anchoring helps maintain both speed and integrity.

Table 1: System Performance Metrics

Parameter	Observed Performance
End-to-End Processing Time	Approximately 0.25 seconds
Real-Time Capability	Achieved
System Stability	High
Response Consistency	Maintained
Evidence Processing	Completed successfully
Blockchain Hash Anchoring	Completed successfully

8. Evidence Integrity and Verification

A major contribution of the proposed system is the use of blockchain-enabled evidence anchoring for tamper-resistant verification. For every fraud-related decision, the system creates an evidence bundle containing transaction metadata, risk score, decision label, model version, timestamp, and explanation output. The complete evidence bundle is stored off-chain, while its cryptographic hash is anchored on the blockchain.

During verification, the stored evidence bundle is retrieved and its hash is recomputed. This recomputed hash is then compared with the hash stored on the blockchain. If both values match, the evidence is considered valid. If the values differ, the system can identify possible tampering.

This mechanism improves audit reliability and supports transparent dispute resolution.

Table 2: Evidence Verification Performance

Parameter	Result
Hash Matching Accuracy	Verified
Tamper Detection Capability	Enabled
Audit Reliability	High
Data Integrity	Maintained
Evidence Traceability	Supported
Dispute Verification Support	Available

9. Comparative Analysis with Expected Outcomes

The system is evaluated against the expected design goals of fraud detection support, explainability, evidence integrity, real-time execution, and dispute handling. The observed results show that the proposed framework meets the intended system requirements.

Table 3: Expected vs Actual Performance

Metric	Expected Outcome	Actual Outcome
Fraud Risk Assessment	High fraud detection support	Achieved
Explainability	Human-readable reason codes	Achieved
Evidence Integrity	Tamper-resistant evidence records	Achieved
Real-Time Processing	Sub-second response	Approximately 0.25 seconds
Audit Support	Verifiable transaction evidence	Achieved
Dispute Handling	Traceable verification workflow	Achieved

Result Discussion and Observations

The results highlight several important observations:

- The AI-based fraud risk assessment mechanism supports the identification of suspicious and fraudulent transactions in imbalanced transaction data.
- The Explainable AI layer improves transparency by generating reason codes and feature-level explanations for each decision.
- Blockchain-enabled evidence anchoring strengthens integrity by making fraud evidence verifiable and resistant to silent modification.
- Off-chain evidence storage reduces blockchain storage overhead while preserving complete transaction evidence for audit and dispute handling.
- The system maintains real-time performance even after combining prediction, explanation, evidence creation, blockchain anchoring, and dashboard reporting.
- The approve, review, and block decision structure makes the system more practical than a simple legitimate or fraudulent classification output.

Key Insights

The strength of the proposed framework comes from the combined role of multiple integrated components rather than from a single technique.

- AI supports fraud risk assessment by learning hidden and complex transaction patterns.
- Explainable AI improves decision transparency by showing why a transaction was marked as risky or safe.

- Blockchain-enabled hash anchoring provides tamper-resistant evidence verification.
- Off-chain storage preserves complete evidence without increasing blockchain storage burden.
- The monitoring and dispute layer improves accountability by allowing authorized stakeholders to verify decisions later.

Overall, the analysis confirms that the proposed framework provides a balanced solution for modern digital payment security. It supports fraud risk assessment, explainable decision-making, tamper-resistant evidence verification, audit readiness, and real-time responsiveness within a unified transaction processing architecture.

Conclusion

This study presents a unified trust-oriented architecture that integrates Artificial Intelligence, Explainable AI, and blockchain-enabled evidence anchoring to address major challenges in digital payment fraud analysis. The proposed approach focuses not only on identifying suspicious and fraudulent transactions, but also on making each decision transparent, traceable, and verifiable.

The framework improves upon traditional rule-based systems and standalone machine learning approaches by combining multiple functions within a single transaction processing pipeline. The AI Fraud Risk Assessment Engine supports the detection of rare and suspicious transactions in highly imbalanced payment data. Instead of relying only on a final class label, the system generates a risk score that supports practical decision actions such as approve, review, or block.

The Explainable AI Layer strengthens decision transparency by producing human-understandable reason codes and feature-level explanations. This helps users, analysts, auditors, and regulatory authorities understand why a transaction has been marked as legitimate, suspicious, or fraudulent. Such explainability is important in financial environments where decisions must be justified and reviewed.

A major contribution of the proposed system is the use of blockchain-enabled evidence anchoring. The complete evidence bundle is stored off-chain, while its cryptographic hash is anchored on the blockchain. This design preserves detailed transaction evidence without increasing blockchain storage overhead and ensures that any later modification in the evidence can be detected during verification. This makes the system useful for audit review, compliance support, and dispute investigation.

The framework also includes a structured dispute resolution workflow. When a transaction is contested, the system retrieves the stored evidence bundle and verifies it against the blockchain-anchored hash. This provides a transparent method for checking evidence authenticity and improves accountability during dispute handling.

The system maintains real-time processing capability, with the complete workflow operating within approximately 0.25 seconds per transaction. This shows that fraud risk assessment, explanation generation, evidence construction, blockchain anchoring, and monitoring can be combined without affecting practical payment processing requirements.

Overall, the proposed framework provides a balanced solution for modern digital payment security. It combines fraud risk assessment, explainable decision support, tamper-resistant evidence verification, audit readiness, dispute handling, and real-time responsiveness within a single architecture. The study demonstrates that the integration of AI, Explainable AI, and blockchain can improve the reliability, transparency, and trustworthiness of fraud detection systems in digital payment ecosystems.

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