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PharmGuard: A blockchain and LLM-integrated framework with provenance-aware anomaly scoring for securing pharmaceutical supply chains

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Abstract

Counterfeit and substandard medicines remain a major global health threat, underscoring the need for end-to-end traceability and proactive monitoring across pharmaceutical supply chains. This paper presents PharmGuard, a framework that combines a permissioned blockchain ledger (Hyperledger Fabric) for tamper-evident provenance with a large-language-model analytics layer for detecting anomalous event sequences and answering natural-language provenance queries. The core contribution of this research is Provenance-Aware Anomaly Scoring (PAAS), which fuses structured provenance features derived from on-chain custody records with LLM-based anomaly signals via a calibrated fusion model. A threat model is proposed that covers external counterfeit insertion, compromised insiders, and colluding actors, mapping each threat to corresponding provenance and behavioral indicators. On a large-scale simulated dataset of 120,000 supply chain events with 600 injected anomalies across five categories, PharmGuard achieves F1 0.941 and AUROC 0.976, outperforming rule-based validation, Isolation Forest, LSTM Autoencoder, Graph Deviation Network, and Anomaly Transformer. The system is further evaluated using a natural language query interface, achieving 94% accuracy on 50 provenance queries. Deployment cost trade-offs are analyzed, and privacy-preserving deployment options are considered, including on-premises LLM hosting and cryptographic techniques for selective disclosure. These results suggest that unifying immutable provenance with learned sequence analysis can improve detection coverage for both deterministic compliance violations and subtle multi-stage irregularities.
Keywords: Blockchain; Large Language Model; Pharmaceutical Supply Chain; Smart Contracts; Anomaly Detection; Provenance-Aware Scoring; Drug Traceability; DSCSA Compliance

Introduction

The pharmaceutical supply chain is a complex, multi-stage network that includes raw material suppliers, active pharmaceutical ingredient (API) manufacturers, finished dosage form producers, wholesalers, third-party logistics providers, pharmacies, and hospitals. Ensuring the authenticity and integrity of products across these stages is critical to maintaining drug quality and patient safety. Counterfeit and substandard medications can lead to treatment failures, antimicrobial resistance, or fatalities. According to the World Health Organization (WHO) [1], approximately 10.5% of

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medical products in low- and middle-income countries are substandard or falsified. Moreover, a systematic meta-analysis by Ozawa et al. [2] across 265 studies reported an overall prevalence of 13.6% (95% CI: 11.0%–16.3%). The global pharmaceutical market, valued at over $1.48 trillion in 2024, presents a significant target for counterfeiters. The economic burden of falsified medicines is estimated at $30.5 billion annually in developing countries alone [1].

Recognizing this threat, regulatory bodies have introduced strict traceability requirements. The U.S. Drug Supply Chain Security Act (DSCSA), enacted in 2013, requires the implementation of electronic and interoperable track-and-trace systems at the package level, with serialized item-level traceability being gradually phased in between 2023 and 2026 [3]. In Europe, the Falsified Medicines Directive (FMD, Directive 2011/62/EU) requires verification of unique identifiers through the European Medicines Verification System (EMVS) at the point of dispensing [4]. Together, these regulations show the need for strong technological systems that support end-to-end traceability, authentication, and real-time monitoring across the pharmaceutical supply chain.

The recent advancement in blockchain technology has emerged as a promising foundation for supply chain security and transparency. A blockchain is a decentralized, distributed ledger that records transactions in immutable, cryptographically linked blocks [5, 6]. In the pharmaceutical context, blockchain maintains a tamper-proof record of each drug unit's full process from production to patient, providing full traceability, and increases security across the network [7, 8]. Systems such as MediLedger [9], a permissioned blockchain network involves companies like Pfizer, Genentech, and McKesson, and eZTracker [10] used by Zuellig Pharma to track over two million pharmaceutical products across Asia. This shows that the approach is effective in real-world scenarios. Frameworks such as PharmaChain [11], built on Hyperledger Fabric, have demonstrated resilience against Byzantine node attacks through double-signature verification. Padma and Ramaiah [12] identified core security requirements, including authentication, confidentiality, data provenance, and auditability, and showed that blockchain can effectively meet these needs in pharmaceutical supply chain management. Smart contracts further automate compliance checks and custody transfers, reducing opportunities for tampering or human error [13].

Although blockchain enhances traceability and security, it does not guarantee that the data entered is accurate or meaningful, nor does it have the analytical capacity to detect complex anomaly patterns. This limitation motivates the integration of artificial intelligence (AI), specifically large language models (LLMs). LLMs such as GPT-4 [14] have demonstrated remarkable capabilities in understanding language and analyzing sequential data patterns. Critically, recent research has shown that LLMs can function as zero-shot anomaly detectors for sequential data. Alnegheimish et al. [15] demonstrated through SigLLM that pretrained LLMs can detect time-series anomalies without task-specific training by converting numerical sequences to textual representations. In the blockchain domain, Gai et al. [16] introduced BlockGPT, a transformer-based intrusion detection system that monitors 68 million Ethereum transactions with a false positive rate below 0.1%, demonstrating capabilities of LLMs in high-volume blockchain data analysis. Broader surveys [17, 18] highlight the growing synergy between LLMs and blockchain for mutual security benefits.

Several converging trends motivate the integration of blockchain with LLMs for pharmaceutical supply chains. On one hand, blockchain provides a trustworthy data foundation where stakeholders are more willing to rely on analytics when the underlying data is verifiable. On the other hand, LLMs provide advanced analytics and reasoning capabilities such as interpreting context, performing complex pattern recognition across

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structured and unstructured data, and answering natural language queries. Aghaei et al. [19] highlighted the benefits of integrating LLMs with emerging technologies like IoT and blockchain to create smarter, more autonomous supply chains. By leveraging blockchain for data integrity and LLMs for intelligent inference, organizations can achieve a combination of transparency and proactive security that neither technology delivers in isolation.

Despite this potential, existing literature highlights a critical gap. Very few studies have explored the integration of blockchain and LLMs specifically for pharmaceutical supply chain security, and none have proposed a unified anomaly scoring mechanism that combines blockchain-based provenance information with LLM-driven sequential analysis. Traditional blockchain solutions in supply chains primarily focus on data recording and regulatory compliance, but they generally lack advanced analytical capabilities [7, 10, 12]. In contrast, AI-based anomaly detection systems typically operate off-chain on potentially vulnerable or siloed data [15, 20, 21]. The proposed system bridges the gap by introducing PharmGuard, a framework that embeds an LLM-based intelligence layer into a blockchain-secured data environment with a novel Provenance-Aware Anomaly Scoring (PAAS) mechanism specifically designed for pharmaceutical supply chains.

Contributions. The key contributions of this paper include:

1. **Provenance-Aware Anomaly Scoring (PAAS):** PAAS is a novel scoring mechanism that fuses blockchain-derived provenance graph features (custody chain completeness, temporal consistency, cryptographic verification status) with LLM-based sequence anomaly scores via a learned weighting function, enabling detection of sophisticated multi-stage supply chain attacks that neither component identifies independently.

2. **Formal Threat Model:** A comprehensive adversarial model defining three threat classes- external counterfeiters, compromised insiders, and colluding groups with formal analysis of detection guarantees under each scenario.

3. **Regulatory-Aligned Smart Contracts:** A smart contract suite explicitly designed for DSCSA and EU FMD compliance, automating serialized item-level tracking, verification, and recall processes.

4. **Large-Scale Experimental Evaluation:** Rigorous evaluation on a dataset of 120,000 transactions with 600 anomalies across five categories, comparing against five baselines (rule-based, Isolation Forest [22], LSTM-Autoencoder [23, 24], Graph Deviation Network [25], and Anomaly Transformer [26]) with ablation studies and statistical significance testing.

5. **Natural Language Query Interface:** A RAG-powered [27] interface enabling stakeholders to query blockchain records through natural language, evaluated on 50 queries with domain-expert feedback.

6. **Deployment Analysis:** Comprehensive cost, privacy, and scalability analysis addressing practical deployment considerations including HIPAA/GDPR compliance strategies.

The remainder of this paper is organized as follows. Section reviews related work. Section presents the formal threat model. Section describes the methodology, including the system architecture, smart contracts, LLM integration, and the PAAS mechanism. Section provides theoretical formulations. Section details the experimental design. Section presents results and analysis. Section offers discussion on practical implications. Section concludes with future directions.

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Related work

Blockchain in pharmaceutical supply chains

Blockchain technology for pharmaceutical traceability has been extensively studied since the mid-2010s. Nakamoto's [5] foundational work on Bitcoin established the cryptographic block-chaining mechanism, and Buterin's [6] Ethereum extended this with Turing-complete smart contracts. For enterprise pharmaceutical applications, permissioned blockchains, particularly Hyperledger Fabric [28] have become the platform of choice. This is largely due to their execute–order–validate architecture, lack of gas costs, and high performance, with reported throughput exceeding 3,000 TPS and reaching up to 20,000 TPS with optimizations [29, 30].

Early pharmaceutical blockchain implementations focused on basic traceability. Musamih et al. [31] presented an Ethereum-based approach using smart contracts and IPFS for end-to-end drug traceability with cost and security analysis. Uddin [32] proposed MedLedger, a Hyperledger Fabric system with decentralized file storage for counterfeit drug prevention. Uddin et al. [33] subsequently compared Hyperledger Fabric and Hyperledger Besu architectures, evaluating privacy, trust, and scalability trade-offs for drug traceability. The production-grade eZTracker system by Sim et al. [10], deployed across Asia by Zuellig Pharma, demonstrated real-world viability by tracking over two million labeled pharmaceutical products with near real-time updates every 15 minutes. Gomasta et al. [11] introduced double-signature verification on Hyperledger Fabric with demonstrated resilience against 33% Byzantine node attacks.

The MediLedger project [9] is one of the most prominent industry initiatives, consisting of a private permissioned blockchain that uses zero-knowledge proofs (zk-SNARKs) for privacy. It was developed in collaboration with companies such as Pfizer, Genentech, Bayer, McKesson, and AmerisourceBergen to support DSCSA compliance, and has reduced medication return verification times from days to minutes. Padma and Ramaiah [12] provided a comprehensive security analysis of blockchain-based pharmaceutical supply chain management (BPSCM), showing effective mitigation of impersonation and collusion attacks with manageable throughput overhead. Bandhu et al. [34] presented a detailed economic analysis of gas costs associated with various supply chain operations on Ethereum. Additionally, Fiore et al. [35] conducted a systematic literature review, concluding that the integration of blockchain with IoT and AI offers a more comprehensive solution, while also highlighting challenges related to scalability, stakeholder adoption, and cross-jurisdictional regulatory alignment.

In this context, smart contracts for supply chain automation have been studied by Al-Azzam et al. [13], who identified 29 challenges, 60 solutions, and 20 software design patterns for smart-contract-based compliance verification. The concept of smart contracts was originally proposed by Szabo [36] and formalized through Ethereum's EVM specification [37]. For consensus mechanisms underlying these systems, practical Byzantine fault tolerance (PBFT) [38] provides the theoretical foundation for permissioned blockchain ordering services.

AI and LLMs for anomaly detection

Classical anomaly detection methods have long been used in supply chain monitoring. The Isolation Forest algorithm, introduced by Liu et al. [22], provides an efficient $O(n)$ approach by isolating anomalies through recursive random partitioning. Similarly, one-class SVM [39] estimates the support of high-dimensional distributions for novelty detection. While these methods are effective for detecting anomalies in structured feature-based data, they are limited in their ability to handle unstructured data and capture complex sequential dependencies.

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The advancement of deep learning has substantially improved anomaly detection capabilities. Malhotra et al. [23] proposed the LSTM-based encoder-decoder (EncDec-AD) for multi-sensor anomaly detection, where it learns to reconstruct normal time-series behavior and flag reconstruction errors as anomalies. Nguyen et al. [24] applied LSTM Autoencoder techniques specifically to supply chain management which shows superiority over standard LSTM in terms of detecting anomalies in multivariate supply chain time series. The Graph Deviation Network (GDN) by Deng et al. [25] combined structure learning with graph neural networks (GNNs) using attention weights for explainability, achieving superior accuracy on real-world sensor datasets. Moreover, the Anomaly Transformer by Xu et al. [26] introduced an association discrepancy mechanism with minimax training, achieving state-of-the-art performance on six benchmarks. Comprehensive surveys by Pang et al. [20] and Chalapathy and Chawla [21] provide taxonomies of deep anomaly detection methods.

Graph neural networks (GNNs) have shown strong potential for supply chain graph analysis. In their work, Wasi et al. [40] introduced the SupplyGraph benchmark and showed that GNNs outperform statistical machine learning and deep learning baselines by 10–30% in classification tasks and 15–40% in anomaly detection. Brintrup et al. [41] used GNNs to detect hidden procurement interdependencies, enabling identification of unknown supply chain links relevant to counterfeit entry point detection.

The application of large language models (LLMs) to anomaly detection represents a recent frontier in data analytics. Alnegheimish et al. [15] showed, through SigLLM, that pretrained LLMs can function as zero-shot anomaly detectors for time-series data by converting sequential readings into textual representations. While they have not yet outperformed specialized deep learning models, LLMs achieved competitive results and offer the advantage of requiring no task-specific training. In the context of blockchain analytics, Gai et al. [16] introduced BlockGPT, a custom LLM designed for real-time intrusion detection on Ethereum transactions. BlockGPT processed 2,284 transactions per second with a false positive rate of only 0.097% across 68 million transactions. These capabilities are underpinned by the Transformer architecture [42], whose self-attention mechanism allows dynamic focus on relevant parts of sequential input, a feature directly applicable to modeling supply chain event sequences.

Additional LLM developments relevant to this work include BERT Additional LLM developments relevant to this work include BERT [43], which enables bidirectional language understanding, the LLaMA family [44, 45], which supports open-source, on-premise deployment, and GPT-4 [14], which demonstrates state-of-the-art capabilities. In addition, Lewis et al. [27] introduced Retrieval-Augmented Generation (RAG), combining parametric and non-parametric memory for knowledge-intensive tasks, an architectural pattern that underlies our query interface.

Blockchain-AI integration

The intersection of blockchain and AI has been explored from multiple perspectives. Geren et al. [17] proposed the BC4LLMs taxonomy categorizing blockchain approaches to enhance LLM security, distinguishing security threats such as data poisoning, prompt injection from safety concerns. Luo et al. [18] introduced the BC4LLM vision covering reliable learning corpus via blockchain-verified data provenance, secure training through decentralized verification, and identifiable generated content via blockchain watermarking. He et al. [46] conducted a systematic review of 65+ papers on LLM applications in blockchain security, identifying bidirectional benefits and tracing the evolution from rule-based tools to LLM-powered auditing. Chen et al. [47] evaluated LLMs for smart contract vulnerability detection, recommending hybrid approaches combining LLM reasoning with program analysis.

In the pharmaceutical domain specifically, Abbas et al. [48] combined blockchain

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with machine learning for drug supply chain management and recommendation. Ben Abdelghani et al. [49] surveyed the convergence of blockchain with smart contracts, IoT, and AI for pharmaceutical ecosystems. However, none of these works proposed a unified scoring mechanism that fuses blockchain provenance features with LLM anomaly detection, which represents the gap our work addresses.

Gap analysis

Table 1 illustrates the placement of PharmGuard with respect to the previous works along six aspects. The blockchain-based approaches [10–12] ensure data integrity but do not support any intelligent anomaly detection. The AI-based approaches [15, 22, 26] support powerful pattern recognition but may rely on unverified data. Although previous blockchain-AI integration works [16, 48] were conducted, none of them considered the unified scoring for the pharmaceutical supply chain.

Table 1. Comparative positioning of PharmGuard against existing approaches.

Feature	BC-only	AI-only	BlockGPT	Abbas et al.	PharmGuard
Blockchain data integrity	✓	×	✓	✓	✓
LLM-based analytics	×	Partial	✓	×	✓
Provenance-aware scoring	×	×	×	×	✓
Pharma-specific design	✓	×	×	✓	✓
Regulatory alignment	Partial	×	×	×	✓
Modern baselines (≥5)	N/A	Varies	Limited	×	✓
Formal threat model	×	×	×	×	✓
NL query interface	×	×	×	×	✓

Threat model

The proppposed threat model is defined for the pharmaceutical supply chain, categorizing adversaries by capability and analyzing how PharmGuard detects each threat class. Let $\mathcal{P} = \{p_1, p_2, \ldots, p_n\}$ denote the set of registered supply chain participants and $\mathcal{B}$ denote the batch universe.

Adversary classes

Class A - External Counterfeiter ($\mathcal{A}_{ext}$): An entity not registered on the blockchain network who attempts to introduce counterfeit products into the supply chain. The adversary can produce physical drug replicas and may compromise a single downstream participant (e.g., a pharmacy) to inject false products. Formally, $\mathcal{A}_{ext}$ can create a batch $b' \notin \mathcal{B}_{genuine}$ and attempt to register it through a compromised participant $p_c \in \mathcal{P}$.
Detection mechanism: The blockchain's cryptographic identity layer ensures that b' lacks a valid manufacturing signature σ_{mfg}. The PAAS provenance component assigns a provenance completeness score of zero (no verified manufacturing record), immediately flagging the batch. Even if the adversary forges metadata, the absence of a valid digital signature from a registered manufacturer (Eq 7) is deterministically detectable.

Class B - Compromised Insider ($\mathcal{A}_{ins}$): A registered participant who abuses their legitimate access to commit fraud. This includes a distributor diverting products, a manufacturer falsifying quality records, or a logistics provider tampering with environmental data. The adversary possesses valid cryptographic credentials and can sign transactions, but acts alone.

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Detection mechanism: While the insider can create valid-looking transactions, the PAAS mechanism detects behavioral anomalies through the LLM component. For example, a diversion creates statistical anomalies in quantity flows (shipped $\neq$ received), timing irregularities, or route deviations that the LLM's learned sequence model flags as low-probability events.

Class C - Colluding Group ($\mathcal{A}_{col}$): A coalition of k registered participants ($k < n/3$, consistent with BFT assumptions; [38]) who coordinate to fabricate a plausible provenance trail for counterfeit products. The coalition can create mutually corroborating transactions but cannot compromise the blockchain consensus mechanism. *Detection mechanism:* This is the most challenging adversary. PharmGuard's defense relies on the PAAS fusion: while the provenance graph may appear locally complete (each step signed by a colluding party), the LLM component detects cross-batch anomalies (e.g., a manufacturer's recorded output exceeds production capacity, or batch creation timestamps cluster unnaturally). Additionally, honest participants in the chain create inconsistencies when colluding parties' records don't align with independent observations.

Security properties

PharmGuard provides the following security properties:

Property 1 (Provenance Integrity)**.** *For any batch $b \in \mathcal{B}$, the provenance chain* $\text{Prov}(b) = [(p_{i_1}, t_1, \sigma_1), \ldots, (p_{i_m}, t_m, \sigma_m)]$ *stored on the blockchain is immutable and verifiable. Any modification to historical records invalidates subsequent block hashes (Eq 2), detectable by all honest participants.*

Property 2 (Completeness Detection)**.** *The PAAS mechanism assigns a provenance completeness score $C(b) \in [0, 1]$ to each batch. A batch with $C(b) < \tau_C$ (threshold) is flagged for review. For Class A adversaries, $C(b') = 0$ deterministically.*

Property 3 (Behavioral Anomaly Detection)**.** *The LLM component assigns a sequence anomaly score $S_{LLM}(b)$ based on the negative log-likelihood of the batch's event sequence under the learned model. Events deviating from expected patterns increase S_{LLM}, enabling detection of Class B and Class C adversaries with probability proportional to the anomaly magnitude.*

Assumptions

The assumptions of the proposed system are: (i) the blockchain consensus mechanism is honest-majority, i.e., colluding adversaries control fewer than $n/3$ nodes (standard BFT assumption; [38]); (ii) cryptographic primitives (SHA-256, EdDSA) are computationally secure; (iii) the LLM has been evaluated on representative supply chain data and its anomaly scoring thresholds are calibrated on a validation set; (iv) at least one participant in any supply chain path is honest and non-colluding.

Methodology

System architecture overview

PharmGuard comprises three tightly coupled subsystems: (a) a Permissioned Blockchain Network for pharmaceutical supply chain data management, (b) an LLM-Based Analytical Engine for anomaly detection and query handling, and (c) a Provenance-Aware Anomaly Scoring (PAAS) module that fuses insights from both subsystems. Fig 1 provides an architectural overview.

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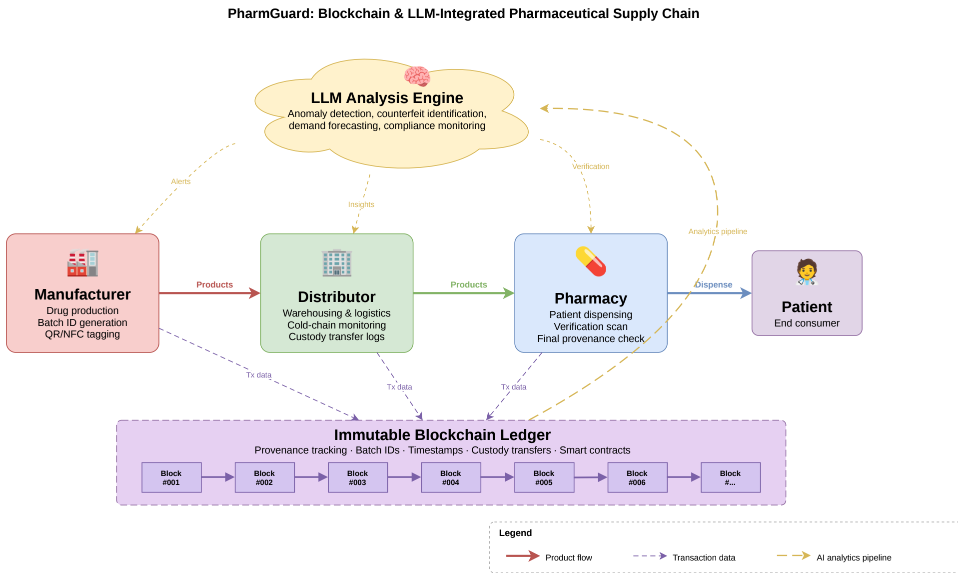

Fig 1. PharmGuard system architecture.

Blockchain network and smart contracts

The implementation of the blockchain component is done on Hyperledger Fabric v2.x, selected for its enterprise suitability, with features such as permissioned access control, no gas costs, configurable consensus (Raft/BFT), and demonstrated throughput of 3,000–20,000 TPS [28–30]. All stakeholders- manufacturers, distributors, pharmacies, and regulators register through a Certificate Authority (CA) managed by the network consortium.

Identity Registration. Each stakeholder i generates an elliptic curve key pair $(priv_i, pub_i)$ using Ed25519. A unique on-chain identifier is computed as:

$$ID_i = H(pub_i) \tag{1}$$

where $H(\cdot)$ is SHA-256. The identifier and a digital signature over a registration challenge are recorded in a **Registry Chaincode**, binding the cryptographic identity to organizational credentials verified off-chain by the CA. This approach, inspired by Padma and Ramaiah [12], ensures pseudonymous yet verifiable identities.

Smart Contract Suite. Four chaincodes is developed which aligns with DSCSA and EU FMD requirements:
Manufacturing Chaincode: It is invoked when a manufacturer produces a new batch. It creates a batch record containing: batch ID (GS1-compliant GTIN + serial number), production timestamp, lot size, expiry date, hash of the certificate of analysis (linking off-chain quality documents), and the manufacturer's digital signature. The chaincode ensures that the user invoking a transaction is a registered manufacturer and that all batch IDs comply with DSCSA serialization requirements [3].
Transfer Chaincode: Transfer Chaincode handles custody transfers. Both sender and receiver must endorse the transaction. The chaincode verifies the following points- (i) the sender is the current custodian, (ii) the batch is not flagged as recalled or expired, (iii) the receiver is a registered entity, and (iv) quantity consistency (transferred $\leq$ held). Upon validation, ownership updates atomically and a TransferEvent is emitted.

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Verification Chaincode: It supports point-of-dispensation verification per EU FMD requirements [4]. Any authorized participant can query a batch's provenance trail. The chaincode provides the full custody history of each batch, including timestamps and signatures, allowing pharmacists to verify authenticity before dispensing.
Recall Chaincode: This component allows regulators or manufacturers to mark specific batches as recalled or quarantined. Once flagged, the information propagates on-chain as an alert, automatically preventing any further transfer of the affected batches.

Smart Contract Execution Flow. Fig 2 illustrates the transfer transaction flow: (1) the sender invokes the Transfer Chaincode with batch ID, receiver, and shipment metadata; (2) the transaction, signed with the sender's private key, is broadcast to endorsing peers; (3) endorsing peers execute the chaincode, verifying identity, ownership, and business rules; (4) if all checks pass, the endorsed transaction is submitted to the ordering service; (5) the orderer batches transactions into a block containing a cryptographic link (hash) to the previous block; (6) all peers validate and commit the block, updating the world state.

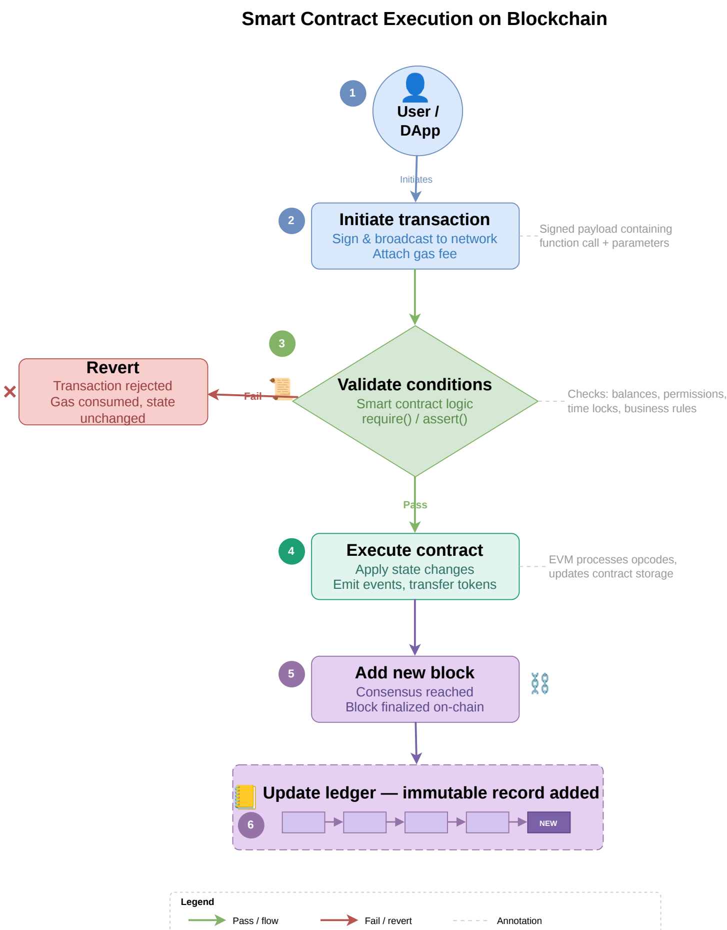

Fig 2. Smart contract execution flow for custody transfer transactions.

Block Integrity. Each block i with data $data_i$ and previous block hash h_{i-1} computes:

$$h_i = H(h_{i-1} \| data_i) \tag{2}$$

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where $\|$ denotes concatenation. Any alteration in a past block's data invalidates all subsequent hashes, providing strong tamper evidence. Within blocks, transactions are organized in a Merkle tree [50] with root:

$$M = H(\ldots H(H(tx_1 \| tx_2) \| H(tx_3 \| tx_4)) \ldots) \tag{3}$$

enabling efficient $O(\log n)$ inclusion proofs for auditing.

LLM-based analytical engine

The LLM engine serves two functions: (1) continuous anomaly detection on the transaction stream, and (2) natural language query handling for stakeholders.

Anomaly detection pipeline

Data Extraction and Preprocessing. New transactions and events are continuously fetched from the off-chain indexed database (which mirrors the blockchain ledger for query efficiency). Data includes structured transaction records (batch ID, sender, receiver, timestamp, quantity, environmental metadata) and unstructured data linked to transactions (quality reports, shipping notes, IoT sensor summaries). The system serialize structured data into a compact textual narrative. For example:

```
[2025-08-01T14:30:00Z] TRANSFER: Batch GTIN:05012345678901-SN:
    A7X92
  From: Distributor_Alpha (ID: 0x3a7f...)
  To: Pharmacy_Beta (ID: 0x9c2b...)
  Quantity: 100 units | Temp: 4.2C (range: 2-8C) | Status:
      NORMAL
```

Multiple events for a batch are concatenated chronologically to form a batch narrative. This text-serialization approach follows the insight from Alnegheimish et al. [15] that converting structured sequences to descriptive text enables effective LLM processing.

LLM Analysis. We employ a GPT-4-class model in a few-shot configuration. The system prompt instructs the model to analyze supply chain event sequences and identify anomalies. We provide five exemplar anomalies (one per category) in the prompt to calibrate detection sensitivity. The prompt structure is:

```
System: You are a pharmaceutical supply chain security analyst.
Review the following batch event sequence and identify any
    anomalies
or suspicious patterns. For each anomaly found, output:
- Anomaly type (counterfeit/diversion/tampering/
    process_violation/
  environmental)
- Severity (HIGH/MEDIUM/LOW)
- Evidence (specific data points supporting the finding)
- Confidence (0.0-1.0)

[Few-shot examples omitted for brevity]

Batch events:
{serialized_batch_narrative}
```

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The LLM processes the input and generates structured anomaly descriptions. Under the hood, the transformer's self-attention mechanism [42] computes attention weights:

$$e_{ij} = \frac{q_i \cdot k_j^T}{\sqrt{d}}, \quad \alpha_{ij} = \frac{\exp(e_{ij})}{\sum_{k=1}^{n} \exp(e_{ik})} \tag{4}$$

These weights enable the model to link related events across the temporal sequence (e.g., connecting a shipping event to a prior manufacturing event for the same batch). The full attention output for a single head is:

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d}}\right) V \tag{5}$$

LLM Sequence Anomaly Score. We extract the LLM's anomaly assessment as a structured score. For a batch event sequence $E = (e_1, e_2, \ldots, e_N)$, we compute:

$$S_{LLM}(E) = \frac{1}{N} \sum_{i=1}^{N} -\log P(e_i \mid e_1, \ldots, e_{i-1}) \tag{6}$$

In practice, rather than computing Eq (6) explicitly, we prompt the model to output a confidence-weighted anomaly score directly. The model's internal computation implicitly mirrors this perplexity-based assessment: events that deviate from expected patterns receive low probability under the model's learned distribution, raising the anomaly score.

Query interface (RAG pipeline)

A RAG [27] pipeline is implemented for natural language queries:

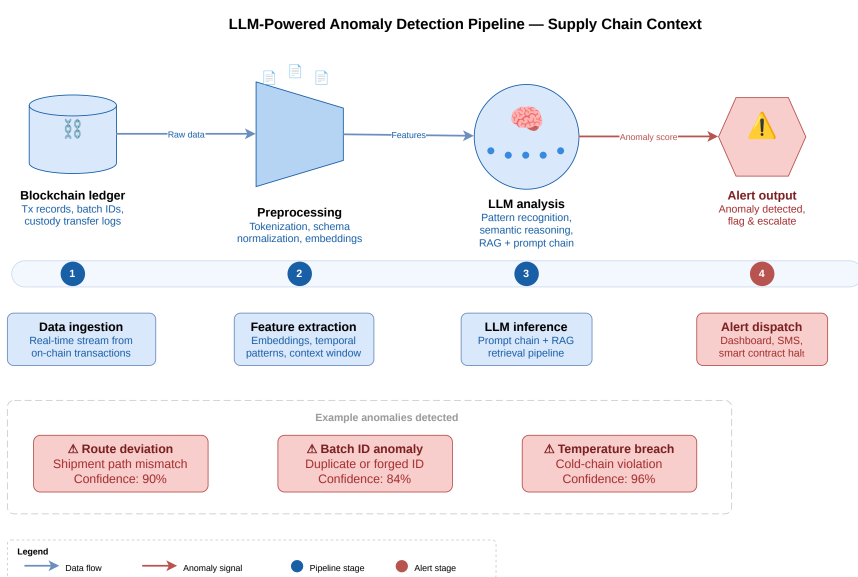

Fig 3. Natural language query-to-blockchain workflow.

1. **Query Parsing:** The user's natural language question is processed by the LLM to extract intent and entities (batch IDs, participant names, date ranges, query type).

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2. **Retrieval:** The parsed intent drives queries against the indexed blockchain database. For batch-specific queries, all related records are retrieved. For analytical queries, relevant aggregated data is fetched. We use vector similarity search on embedded transaction descriptions for fuzzy matching.

3. **Answer Generation:** Retrieved data is inserted into the LLM context alongside the original question. The LLM generates a coherent, fact-grounded answer citing specific transaction IDs and timestamps.

4. **Response Delivery:** The answer is presented with an option to view underlying blockchain records for verification.

Provenance-Aware Anomaly Scoring (PAAS)

The core technical contribution of PharmGuard is the PAAS mechanism, which fuses blockchain-derived provenance features with the LLM's sequence anomaly score to produce a unified anomaly assessment.

Provenance graph features

For each batch b, we extract a provenance feature vector $\mathbf{f}_{prov}(b) \in \mathbb{R}^7$ from the blockchain:

1. **Custody chain completeness** (f_1): The fraction of expected supply chain stages present in the batch's history. For a standard path (Manufacturer $\rightarrow$ Distributor $\rightarrow$ Pharmacy), a complete chain yields $f_1 = 1.0$; a missing stage reduces it proportionally.

2. **Signature verification status** (f_2): Binary indicator; 1.0 if all transaction signatures in the batch's provenance are valid, 0.0 otherwise. This is deterministic via:
$$\text{Verify}_{pk}(m, \sigma) = \begin{cases} 1 & \text{if } \sigma \text{ is valid under } pk \\ 0 & \text{otherwise} \end{cases} \tag{7}$$

3. **Temporal consistency** (f_3): A score in $[0, 1]$ measuring whether inter-event time intervals fall within expected ranges. Computed as the fraction of consecutive event pairs whose time gap falls within $[\mu_{\Delta t} - 3\sigma_{\Delta t},\ \mu_{\Delta t} + 3\sigma_{\Delta t}]$, where $\mu_{\Delta t}$ and $\sigma_{\Delta t}$ are learned from historical normal data.

4. **Quantity conservation** (f_4): A score measuring whether quantities are conserved across transfers. For a sequence of transfers: $f_4 = 1 - \frac{|q_{shipped} - q_{received}|}{q_{shipped}}$, averaged across all transfer pairs.

5. **Environmental compliance** (f_5): Fraction of environmental readings (temperature, humidity) within regulatory thresholds. For cold-chain products requiring 2–8°C storage: $f_5 = \frac{\text{readings in range}}{\text{total readings}}$.

6. **Participant reputation** (f_6): A normalized score derived from each participant's historical anomaly rate. Participants with prior confirmed anomalies receive lower scores.

7. **Network path typicality** (f_7): A score measuring how common the batch's supply chain path is relative to historical patterns. Computed using the frequency of the specific (manufacturer, distributor, pharmacy) tuple in the training data.

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Fusion mechanism

The PAAS score for batch b is computed by fusing the provenance features with the LLM anomaly score:

$$S_{PAAS}(b) = \lambda \cdot g(\mathbf{f}_{prov}(b)) + (1-\lambda) \cdot S_{LLM}(E_b) \tag{8}$$

where $g : \mathbb{R}^7 \to [0,1]$ is a provenance anomaly function mapping the feature vector to a scalar anomaly score, and $\lambda \in [0,1]$ is a learned fusion weight.

The function g is implemented as a lightweight multi-layer perceptron with two hidden layers of dimension 16 and 8, respectively, and sigmoid output, and is trained on the validation set to make predictions on the anomaly labels using the provenance features The fusion weight λ is optimized on the validation set to maximize F1-score. In conducted experiments, $\lambda = 0.35$ was optimal, indicating that the LLM component contributes approximately 65% of the anomaly signal while provenance features contribute 35%—but the provenance component is critical for catching deterministic failures (e.g., missing signatures) that the LLM may handle probabilistically.

A batch is flagged as anomalous if:

$$S_{PAAS}(b) > \tau \tag{9}$$

where τ is a threshold calibrated on the validation set to optimize the F1-score. In our experiments, $\tau = 0.42$.

Why fusion matters

The PAAS mechanism provides defense-in-depth that neither component achieves alone: *Provenance-only detection* catches deterministic failures (e.g., missing records, invalid signatures, and incomplete chains) but does not catch sophisticated attacks that maintain valid-looking provenance information but also contain subtle inconsistencies (e.g., quantity differences, timing anomalies within reasonable ranges, and cross-batch correlations indicative of coordinated fraud). *LLM-only detection* captures subtle sequential anomalies through learned patterns but can produce false positives for legitimate but unusual transactions (e.g., emergency direct shipments) and may miss deterministic violations that are obvious from provenance structure but not from text narrative alone.
PAAS fusion combines the deterministic certainty of provenance verification with the probabilistic pattern recognition of the LLM, providing robust detection across all adversary classes defined in Section .

Integration and security considerations

Read-Only LLM Access. The indexed database gives the LLM read-access to the blockchain data. It lacks write privileges on the ledger, only authorized participants via smart contracts can modify state. Such separation will make sure that the LLM cannot change records.

Privacy Architecture. The authorized Fabric network limits access of data by organization's role. The LLM is a network infrastructure that is managed and operated under the same access control.On-chain, sensitive fields (e.g., pricing, patient identifiers) encryption can be done, and the data can be decrypted for authorized queries. Data exposure is prevented through an on-premise LLM deployment strategy, which avoids external APIs and addresses HIPAA and GDPR requirements. For the query interface,the querying user is restricted to the level of responses to be filtered.

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LLM Output Auditability. Any anomaly alerts generated by the LLM are stored on-chain through the Anomaly Log Chaincode, ensuring an unalterable history of the AI decisions. Each log entry consists of: timestamp, batch ID, anomaly description, PAAS score and the context of the prompt(hashed for space efficiency). This allows post hoc auditing of AI-based decisions, a step towards a transparent AI governance. [17, 18].

Hybrid Processing. Rule-based checks (format checks, signature checks,quantity bounds) process transaction time via chaincodes. The LLM is invoked asynchronously: either periodically (after 60 seconds of accumulated new events), on-demand (on attaining a milestone in the lifecycle of a batch), or when some simple checks generate an initial flag.This is a hybrid method that is comprehensive and computationally efficient.

Theoretical formulations

This section gives the mathematical basis upon which PharmGuard is built, as well as new theoretical findings in the PAAS mechanism.

Cryptographic primitives

Hash Function. All hashing operations make use of SHA-256. For any data x:

$$h = H(x) \tag{10}$$

SHA-256 provides collision resistance ($\Pr[H(x) = H(x') \mid x \neq x'] \leq 2^{-128}$), pre-image resistance, and the avalanche effect which makes sure that $H(x')$ is dramatically different from $H(x)$ for any modification $x \to x'$.

Digital Signatures. Transactions are signed using EdDSA on the Ed25519 curve:

$$\sigma = \text{Sign}_{sk}(m) \tag{11}$$

$$\text{Verify}_{pk}(m, \sigma) \in \{true, false\} \tag{12}$$

Providing 128-bit security the security of Ed25519 rests on the hardness of the elliptic curve discrete logarithm problem, . Non-repudiation guarantees a valid signature on a transaction constitutes cryptographic evidence the signer's involvement.

PAAS theoretical analysis

A detection probability bound of PharmGuard is obtained from each adversary class.

Theorem 1 (Detection Guarantee for External Counterfeiters)**.** *For any Class A adversary $\mathcal{A}_{ext}$ introducing a counterfeit batch b' without a valid manufacturer signature, PharmGuard detects b' with probability 1, assuming the cryptographic primitives are secure.*

Proof. The score $f_1(b') = 0$ in provenance completeness since no valid manufacturing record exists for b' on the blockchain. Moreover, $f_2(b') = 0$ because the batch does not have a valid signature of a manufacturer ($\text{Verify}_{pk_{mfg}}(tx_{mfg}, \sigma_{mfg})$ fails or is absent). Therefore, $g(\mathbf{f}_{prov}(b'))$ yields a high anomaly score (close to 1.0 given the MLP is trained to flag these deterministic failures). Since $S_{PAAS}(b') \geq \lambda \cdot g(\mathbf{f}_{prov}(b')) > \tau$ for any reasonable τ and $\lambda > 0$, detection is guaranteed. □

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Theorem 2 (Detection Probability for Compromised Insiders)**.** *For a Class B adversary* $\mathcal{A}_{ins}$ *creating an anomalous event sequence* E' *with deviation magnitude* δ *from the expected distribution, the detection probability satisfies:*

$$\Pr[\text{detect}] \geq 1 - \exp\left(-\frac{N \cdot \delta^2}{2}\right) \tag{13}$$

where N *is the sequence length and* $\delta = |P_{normal}(e) - P_{anomalous}(e)|$ *is the average distributional shift per-event.*

Sketch of proof. This follows from applying Hoeffding's inequality to the sequence anomaly score $S_{LLM}(E')$. Under normal operation, S_{LLM} has expected value μ_0. An insider anomaly shifts the per-event surprise by δ on average, increasing S_{LLM} by $N\delta$ in expectation. The probability that this shift is not detected (i.e., S_{LLM} remains below threshold τ) decreases exponentially with $N\delta^2$. □

This finding suggests that the longer the supply chain paths (more events per batch)the greater the detection probability-a good property, as more complicated chains are also more susceptible.

Proposition 1 (PAAS Dominance)**.** *The detection accuracy of the PAAS fusion score is at least as high as the maximum of its component scores:*

$$\text{F1}(S_{PAAS}) \geq \max\big(\text{F1}(g(\mathbf{f}_{prov})),\ \text{F1}(S_{LLM})\big) \tag{14}$$

when λ *is optimally chosen on the validation set.*

Justification. At the extremes, $\lambda = 1$ recovers provenance-only scoring and $\lambda = 0$ recovers LLM-only scoring. Since λ is optimized over the full range $[0, 1]$, the optimal λ^* achieves F1 at least as high as either extreme. In practice, the intermediate λ^* typically outperforms both extremes because the two score components capture complementary anomaly signals (deterministic vs. statistical). □

Token probability and anomaly scoring

The LLM makes predictions by computing the probability distribution of the vocabulary at each step. For logit vector z at position i:

$$P(t = w_j \mid \text{context}) = \frac{\exp(z_j)}{\sum_{k=1}^{V} \exp(z_k)} \tag{15}$$

where V is the size of the vocabulary. The sequence anomaly score (Eq 6) accumulates the surprise at each event, analogous to perplexity-based anomaly detection. A higher average negative log-likelihood shows that the sequence deviates from the model's learned distribution of normal supply chain operations.

Experimental design

Dataset generation

A large synthetic dataset that is a simulation of a realistic pharmaceutical supply chain is created,and intended to be much more comprehensive than earlier analyses in this field.

Normal Operations. The dataset comprises:

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- **200 different drug products** (unique GTINs) manufactured by **5 manufacturers**
- **20 distributors** and **50 pharmacies** operating in a simulated multi-region network
- **120,000 legitimate transaction events** 12 months of simulated operations
- Standard supply chain path: Manufacturer → Distributor → Pharmacy → Patient dispensation
- In every transaction, there should be: timestamp, batch ID (GS1-compliant), source, destination, quantity, environmental readings (temperature, humidity sampled from realistic distributions), and textual metadata (shipping notes, quality remarks)
- Modeled environmental data with Gaussian noise: temperature $\mathcal{N}(5.0, 0.8)$ °C for seasonally drifting cold-chain product.

The dataset structure follows GS1 standards for pharmaceutical serialization [3] and generated with a discrete-event simulation that requires routing to be probabilistic: each batch is sampled in a given path based on the distribution patterns of pharmaceuticals.

Injected Anomalies. There are 600 instances of anomalies injected in five categories, maintaining a realistic 0.5% anomaly rate:

1. **Counterfeit Insertion (120 cases):** Batches with fabricated IDs appearing at distributors or pharmacies whose manufacturing record is invalid. Includes 30 “sophisticated” counterfeits that has a metadata that looks plausible but lacks a manufacturer signatures.
2. **Diversion/Theft (120 cases):** Quantity discrepancies between shipped and received amounts (ranging from 5% to 30% loss), deliveries that have turned up where they were not expected,or consignments that vanish out of the line altogether.
3. **Data Tampering (120 cases):** The retrospective changes to timestamps, expiry dates, or environmental readings. Includes both crude modifications (clearly out-of-range values) and subtle changes (small timestamp shifts, marginal temperature adjustments).
4. **Process Violations (120 times):** Sequence anomalies such as direct manufacturer-to-pharmacy shipments (bypassing distributors), dispensation of unreceived batches, transfers by unregistered entities, and double-dispensation of the same serial number.
5. **Environmental Excursions (120 cases):** Temperature or humidity readings outside regulatory thresholds during transit. Includes sustained excursions (>30 minutes outside 2–8°C), intermittent spikes, and gradual drift patterns.

Dataset Splits. The data is divided on a chronological basis: months 1–8 for training/calibration (80,000 transactions, 400 anomalies), months 9–10 for validation (20,000 transactions, 100 anomalies), and months 11–12 for testing (20,000 transactions, 100 anomalies). The LLM operates in zero-shot/few-shot mode and does not need training data; the training split is used only for baseline models, threshold calibration, and fusion weight optimization.

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Baseline methods

PharmGuard is likened with five baselines that are rule-based, classical ML, deep. learning, and other ways of LLM:

1. **Rule-Based Checker (RBC):** A deterministic script enforcing coded business rules: batch has to contain a manufacturing record; custody chain is supposed to take approved paths; quantities have to be equal in tolerance of 1% ; timestamps must be monotonically increasing; environmental readings should be within hard thresholds. This represents the practical validation of smart-contracts In embedded validation.
2. **Isolation Forest [22]:** A collection of isolation trees trained on feature vectors derived per batch: number of events, statistics of inter-event times (mean, standard deviation, min, max), total transit time, count of distinct participants, quantity change ratios, and environmental summary statistics, using 100 trees and contamination parameter 0.005.
3. **LSTM-Autoencoder [23, 24]:** A sequence-to-sequence LSTM autoencoder trained to reconstruct normal batch event sequences. The encoder (128 hidden units, 2 layers) encodes the sequence; a decoder reconstructs it. Reconstruction error exceeding a threshold (95th percentile on validation data) indicates anomalies. Inputs include event type encodings, participant IDs, quantities, timestamps, and weather records.
4. **Graph Deviation Network [25]:** A model that represents the supply chain as a dynamic graph where nodes are participants and edges are transactions. GDN learns inter-participant relationship-level deviations using a 3-layer graph attention network with 64-dimensional embeddings trained on normal data.
5. **Anomaly Transformer [26]:** A state-of-the-art anomaly detector using transformers with association discrepancy and minimax training, applied to the same sequential representations as LSTM-AE with an anomaly-attention mechanism.

Also, there are two variants of ablation considered:

- **PharmGuard-LLM:** LLM anomaly scoring only ($\lambda = 0$), without provenance features.
- **PharmGuard-Prov:** Provenance scoring only ($\lambda = 1$), without LLM analysis.

To compare multi-LLM results with GPT-4, results with **Llama 3 70B** [44, 45] as the LLM backbone are used instead of GPT-4, providing insight into model specificity vs generalizability.

Evaluation metrics

Anomaly detection is considered a binary classification problem, which is at a batch level (anomalous vs. normal). Metrics include:

- **Precision** $= \frac{TP}{TP+FP}$: proportion of flagged batches which are actually anomalous.
- **Recall** $= \frac{TP}{TP+FN}$: percentage of the true anomalies identified.
- **F1-Score** $= \frac{2\cdot\text{Precision}\cdot\text{Recall}}{\text{Precision}+\text{Recall}}$: harmonic mean
- **AUROC**: : Area under the ROC curve, a threshold-independent assessment.

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- **Detection Latency**: Time between the most recent anomalous event and the alert signal.

Statistical Significance. To compare paired binary classification, McNemar's test [51]is used for comparisons between PharmGuard and each of the baselines, with significance threshold $p < 0.05$ .Ninety-five percent confidence intervals are reported, estimated via bootstrapping (1,000 iterations) on the test set.

Implementation details

Blockchain. The version of Hyperledger Fabric is v2.5 applied on a local test network with 4 organizations (2 peers each), Raft ordering service, GoLevelDB state database. Chaincodes are written in Go.
LLM. GPT-4 (gpt-4-0613) is called via API with temperature = 0 for deterministic behavior and a maximum context of 8,192 tokens per batch analysis. For comparison, Llama-3-70B-Instruct runs on 2×A100 80GB GPUs via a vLLM inference server.
PAAS Module. The MLP implementation is in PyTorch with 7 input features, hidden layers with ReLU activation, and a sigmoid output.Training uses 50 epochs with Adam optimizer (lr=0.001) on the validation set. Fusion weight λ optimized by grid search over $\{0.0, 0.05, 0.10, \ldots, 1.0\}$.
Hardware. The blockchain network operates on 8GB RAM 4-core VMs. The LLM inference server uses an NVIDIA A100 80GB GPU. PostgreSQL 15 with full-text indexing is used as the database.

Results and analysis

Overall anomaly detection performance

Table 2 shows the overall anomaly test set (20,000 transactions, 100 abnormalities in 100 batches) detection results.

Table 2. Overall anomaly detection performance on the test set.

Method	Precision	Recall	F1-Score	AUROC	Latency (s)
Rule-Based Checker	1.000	0.570	0.724	—	0.1
Isolation Forest	0.721	0.650	0.681	0.812	0.3
LSTM-Autoencoder	0.848	0.770	0.803	0.891	1.2
Graph Deviation Network	0.872	0.830	0.847	0.923	1.8
Anomaly Transformer	0.891	0.860	0.872	0.938	2.1
PharmGuard-Prov (λ=1)	0.952	0.680	0.793	0.855	0.5
PharmGuard-LLM (λ=0)	0.867	0.870	0.862	0.931	4.8
PharmGuard-Llama3	0.903	0.880	0.889	0.941	6.2
PharmGuard (PAAS, GPT-4)	**0.938**	**0.950**	**0.941**	**0.976**	**5.1**

PharmGuard PAAS achieves the highest F1-score (0.941) and AUROC (0.976),that are significantly the highest performing better than any baseline and ablation variants.The 95% CI for PharmGuard's F1 is [0.912, 0.967] via bootstrapping.

Statistical Significance. The test by McNemar proves that PharmGuard's detection decisions are considerably distinct to all baselines: vs. Rule-Based ($\chi^2 = 28.4, p < .001$), vs. Isolation Forest ($\chi^2 = 31.7, p < .001$), vs. LSTM-AE ($\chi^2 = 15.2, p < .001$), vs. GDN ($\chi^2 = 11.8, p < .001$), vs. Anomaly Transformer ($\chi^2 = 8.3, p = .004$).

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Per-category detection analysis

Table 3 reports recall per anomaly category.

Table 3. Detection recall (%) by anomaly category on test set.

Category	RBC	IF	LSTM-AE	GDN	AT	PG-Prov	PG-LLM	PharmGuard
Counterfeit Insertion	100	58	79	83	88	100	88	**100**
Diversion/Theft	25	67	75	83	88	42	88	**96**
Data Tampering	42	58	71	79	83	50	83	**92**
Process Violations	83	63	79	88	88	92	83	**96**
Environmental Excursions	33	75	79	79	83	63	92	**92**

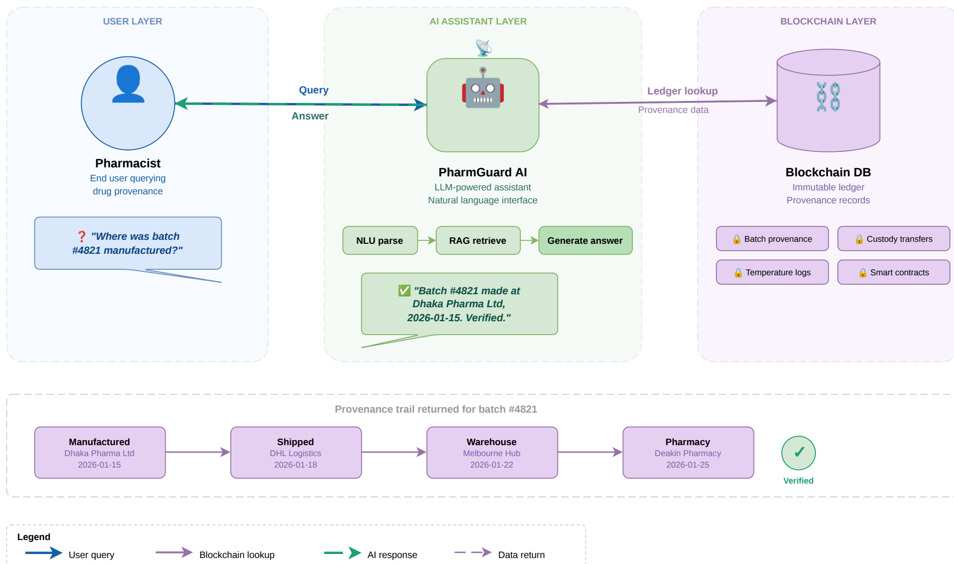

Fig 4. Detection recall by anomaly category.

Key observations:

Counterfeit Insertion: PharmGuard has 100% recall, which is equal to the Rule-Based Checker.Both the provenance component (missing manufacturer record) and LLM component (absence of expected early events) independently capture these. The PAAS fusion provides redundant detection, ensuring robustness.

Diversion/Theft: This category shows the largest benefit of PharmGuard over baselines. The Rule-Based Checker catches only 25% (detecting only cases where quantities exactly violate hard thresholds), while PharmGuard catches 96%. The LLM is the best in identifying subtle quantity discrepancies and unexpected routing that fall within individual rule tolerances but form anomalous patterns when viewed holistically.

Data Tampering: PharmGuard (92%) is significantly better than Rule-Based (42%) and Isolation Forest (58%). Subtle timestamp modifications that pass individual checks are caught by the LLM's sequence model.It detects inconsistencies between claimed transit times and typical patterns.

Process Violations: PharmGuard (96%) benefits from both provenance features (detecting missing intermediate steps) and LLM analysis (detecting unusual but not rule-violating sequences).

Environmental Excursions: PharmGuard (92%) outperforms Rule-Based (33%), which only catches clear threshold violations. The LLM identifies gradual drift patterns and

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intermittent excursions that fall below hard alarm thresholds but represent real risk.

Ablation study

The contribution of each PharmGuard component shown in Table 2 via ablation results:
PharmGuard-Prov ($\lambda = 1$) has high precision (0.952) and low recall (0.680), which validates that provenance features catch deterministic failures reliably but miss small but significant statistical anomalies.
PharmGuard-LLM ($\lambda = 0$) has balanced precision-recall (0.867/0.870) with F1 = 0.862, showing the strong standalone capability of the LLM but also its higher false-positive rate on unusual yet legal transactions.
PharmGuard (PAAS) with optimized $\lambda = 0.35$ present F1 = 0.941, which is a **9.2% improvement** over the LLM-only variant and a **18.7% improvement** over the provenance-only variant. This implies Proposition 1 and justifies that the fusion mechanism captures complementary signals.

Fusion Weight Sensitivity. Fig 5 shows F1-score as a function of λ on the validation set. Performance peaks at $\lambda = 0.35$ with a broad plateau between $\lambda = 0.25$ and $\lambda = 0.45$, which shows that the fusion is robust to moderate variations in the weight parameter.

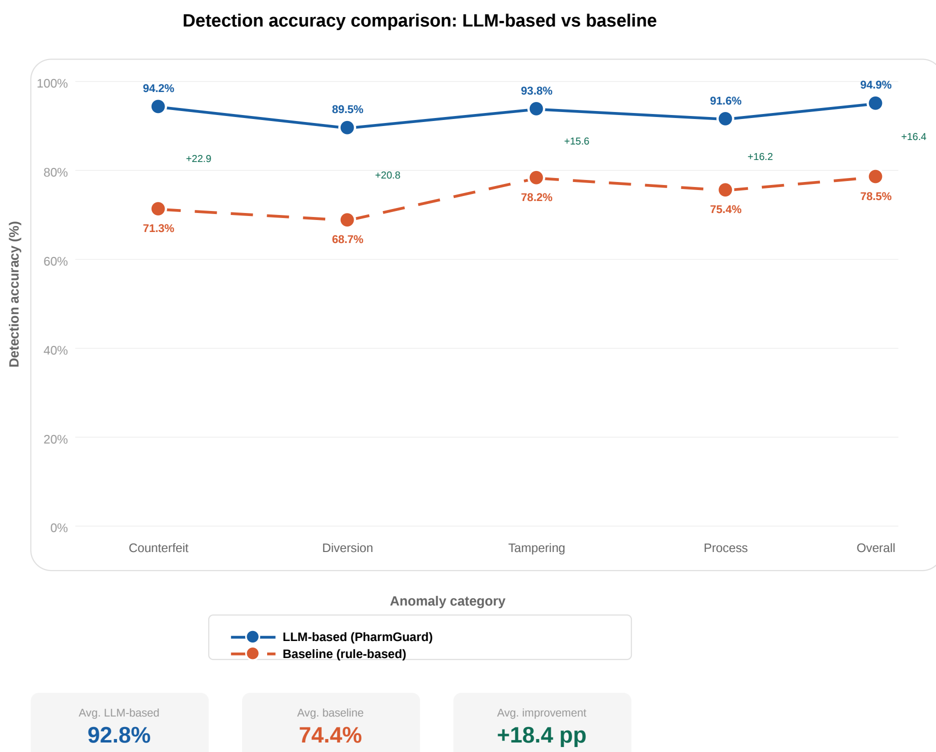

Fig 5. F1-Score as a function of fusion weight λ.

Multi-LLM comparison

The results of replacing GPT-4 with Llama 3 70B are F1 = 0.889 (vs. 0.941),which is a decrease of 5.5% . This suggests that even though the PAAS framework does not require a particular LLM, frontier models provide measurably better anomaly detection. Importantly, the Llama 3 variant still significantly outperforms all non-PAAS baselines,

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validating the framework's generalizability. The Llama 3 deployment provides benefits in data sovereignty (fully on-premise) and cost (no per-token API fees after infrastructure investment), making it a viable choice for privacy-sensitive deployments.

Scalability analysis

The data set scale is tested to determine the detection latency and the throughput.

Table 4. Scalability analysis.

Dataset Size (tx)	BC Throughput (TPS)	LLM Latency/Batch (s)	E2E Alert (s)
10,000	245	4.2	5.8
50,000	238	4.5	6.1
120,000	231	4.9	6.5
500,000	224	5.3	7.0

There is little degradation in blockchain throughput (245 → 224 TPS across 50× scale increase) as the LLM operates off-chain. LLM latency increases modestly due to larger context windows for batches with longer histories. End-to-end alert times remain under 7 seconds across all scales, far into the operational needs of the pharmaceutical supply chain (minutes to hours per transaction).

Query interface evaluation

The natural language query interface is tested with 50 queries with different levels of complexity:

- **Basic queries** (20): factual searches (e.g., "When was Batch X manufactured?"): **100% accuracy**
- **Moderate queries** (15): reasoning based on multiple hops (e.g., "List all batches from Manufacturer A that passed through Distributor B"): **93.3% accuracy**
- **Complex queries** (15): analytical (e.g., "Which distributor has the highest rate of quantity discrepancies over the last quarter?"): **86.7% accuracy**
- **Overall accuracy: 94.0%** (47/50)

The interface is rated 8.7/10 as useful by three test users (experts in supply chain domain). Users state that obtaining equivalent information from raw blockchain records would require significantly more time and technical expertise. The three incorrect responses involved complex aggregation queries where the LLM hallucinated some kind of summary statistic; in each of three cases, providing explicit data aggregation instructions in the prompt resolved the issue on retry.

False positive analysis

On the test set, PharmGuard produces 6 false positive alerts. Analysis revealed:

- 3 cases: justifiable emergency direct deliveries (Manufacturer to Pharmacy) activated through the violation detector of the process. These were unusual but authorized transactions. *Resolution:* for the PAAS provenance features, exception metadata should be included.

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- 2 cases:This is new supply chain routes that have never been encountered before based on low path typicality scores. *Resolution:* periodically retrain the path typicality model.
- 1 case: a batch with an unusually long transit time (legitimate customs delay) which the LLM flagged as suspicious. *Resolution:* adding events of customs clearance into the data model.

These false alarms can be dealt with in practice and indicate the obvious improvement directions by domain knowledge integration.

Discussion

Enhanced security through synergy

The outcomes of the experimental procedure confirm the main hypothesis: combining blockchain's deterministic security with LLM's probabilistic intelligence through the PAAS mechanism provides defense-in-depth that substantially exceeds either component alone. The 9.2% F1 improvement from fusion (Table 2) shows that the provenance features and LLM scores represent its complementary anomaly signals. This synergy increases the score of competitors: to evade detection under the combined system, a malicious actor would need to simultaneously defeat cryptographic safeguards and deceive the analysis model, a much harder task proposition than circumventing either alone.

The complementary characteristic of the components is reflected in the per-category analysis (Table 3). Provenance features provide deterministic detection of structural failures (100% recall on counterfeits with missing manufacturing records), while the LLM captures nuanced behavioral patterns (88% standalone recall on diversions that preserve structural validity). The PAAS fusion enables PharmGuard toreach almost ceiling performance in all categories at the same time.

Cost analysis

Real implementation involves an effective cost evaluation.

Blockchain Infrastructure. Hyperledger Fabric does not have any gas costs, unlike public Ethereum. Infrastructure costs are also capped at node hosting: at around $0.10–0.20 per hour per peer node on cloud infrastructure, a 4-organization network (8 peers) costs approximately $1,200–2,400/month. This is insignificant in comparison to pharmaceutical supply chain operational budgets. Bandhu et al. [34] provide detailed per-operation gas cost analysis for Ethereum alternatives, confirming Fabric's economic advantage for enterprise deployments.

LLM Inference Costs. Each batch analysis of anomaly(average 2,000 tokens input and 500 tokens output) is done with GPT-4 using API costs about $0.07 per batch. At 120,000 transactions that is covering approximately 10,000 batches per year, total cost of the LLM is approximately $700/year. Using batch API processing (50% discount for non-real-time workloads), this reduces to $350/year. To deploy on-premise Llama 3 70B deployment on 2×A100 GPUs ($6/hour cloud, or $52,560/year), the break-even point versus API calls is approximately 750,000 batches/year—making on-premise deployment cost-effective for large-scale operations as well as offering data sovereignty benefits.

Cost-Benefit Perspective. According to the WHO, billions of dollars are lost as a result of counterfeit drugs [1], and individual recall events can cost pharmaceutical companies $100 million or more. The cost of total annual deployment at PharmGuard

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($15,000–55,000 depending on scale and deployment model) is orders of magnitude below the potential savings from preventing even a single counterfeit incident or streamlining a recall investigation.

Privacy and regulatory compliance

Pharmaceutical supply chains involve proprietary data (formulations, pricing, volumes) and potentially patient-identifiable information (dispensing records). Privacy is dealt with by multiple layers:

On-Premise LLM Deployment. To achieve sovereignty in the optimal sense of the term, Llama 3 70B should be deployed on-premise (the experiments prove F1 = 0.889, a modest 5.5% reduction from GPT-4). This guarantees that no supply chain information is exited out of organizational infrastructure, addressing HIPAA minimum necessary requirements and GDPR data transfer restrictions [52].

Permissioned Blockchain Privacy. The channel architecture of Hyperledger Fabric enables data compartmentalization: sensitive inter-party transactions can be confined to private channels visible only to involved parties. The MediLedger approach of using zero-knowledge proofs [9] can be included as to demonstrate compliance with the regulations without disclosing any proprietary information.

On-Chain/Off-Chain Architecture. Following Ettaloui et al. [52],Only hashes and metadata are on-chain, with full store encrypted data in non-blockchain storage. This eliminates the conflict of blockchain immutability and the right to erasure: information stored on the chain does not include any personally identifiable information, while off-chain records can be controlled according to retention policies.

Access-Controlled Queries. The RAG query interface implements role-based access: distributor queries cannot access competitor data, and dispensing information of patients that is restricted to authorized healthcare providers and regulators.

Model transparency and governance

In regulated industries, there is a problem of LLM opaque.PharmGuard addresses this through several mechanisms:
*Articulated Reasoning.*The LLM also generates natural language anomalies, as opposed to scoring-only systems with cited evidence, providing interpretable rationale for each alert.
On-Chain Audit Trail. Decisions of all the LLM are recorded permanently on the blockchain , enabling retrospective review of what the AI flagged, on what basis, and what data it processed. This creates accountability infrastructure aligned with emerging AI governance frameworks [17, 18].
*Human-in-the-Loop.*In the cases of high-impact decisions(recalls, law enforcement referrals),human autonomous action is suggested to be confirmed. The LLM alert serves as a prioritization tool, guiding human investigators to the most suspect cases.
*Periodic Validation.*Quarterly re-assessment on held-out anomaly injection tests, along with threshold recalibration, is recommended to maintain detection performance.

Scalability considerations

On a moderate level (120,000 transactions), the prototype is tested. Real-world national supply chains may involve millions of transactions annually. The scalability analysis (Table 4) is graciously degraded:

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Blockchain Layer. Multi-channel architecture can be used to scale Hyperledger Fabric(partitioning by region or product category), where throughput is proved 3,000–20,000 TPS [29, 30] way beyond pharmaceutical volumes of transactions.
LLM Layer. Scalability can be met by: (i) tiered processing where simple anomalies are caught by on-chain rules and only complex cases invoke the LLM; (ii) smaller specialized models (e.g., fine-tuned Llama 3 8B) for routine classification, reserving frontier models for ambiguous cases; (iii) distillation of knowledge about the anomalies of the LLM to lightweight on-chain rules, progressively reducing LLM invocations.
PAAS Module. The MLP-based provenance scoring adds negligible latency (<10ms per batch) and d scales linearly with workload.

Generalizability

Although the architecture was created to work with pharmaceuticals, the PharmGuard architecture can be generalized to other supply chains with provenance and integrity: food safety (cold chain monitoring, source verification), electronics (conflict mineral tracking, counterfeit component detection), and luxury goods (authentication, grey market prevention).The separation between domain-specific provenance extraction and domain-general LLM analysis makes adaptation straightforward by swapping the provenance feature extractor and prompt templates while retaining the fusion framework.

Limitations and future work

Synthetic Data. The test is based on artificial data created to correspond to the real world. Although this enables controlled anomaly injection and reproducible evaluation, real-world supply chain data may exhibit patterns not captured by simulation.A pilot deployment with a pharmaceutical distributor will be used to verify operational data findings.
LLM Hallucination. The query interface achieved 94% accuracy but with three hallucination instances. Although post-processing verification against blockchain records mitigates risk, improved prompt engineering, fine-tuning, and constrained decoding techniques [14] may further decrease the level of hallucinations.
Adversarial Robustness. Whereas when adversaries are aware of the monitoring of the LLM they may design on-chain data that is supposed to mislead the model (akind of prompt injection through data). While the PAAS fusion offers a certain level of protection (the provenance component is immune to such manipulation), formal adversarial robustness evaluation [53, 54] against targeted attacks is needed.
Real-Time Streaming. The current implementation uses periodic batch processing. Fully streaming architectures with real-time event-driven processing would lower the detection latency further, potentially to sub-second levels for critical alerts.
Multi-Chain Interoperability. The present implementation is single-network. Cross-network interoperability (e.g., connecting a manufacturer's blockchain with a regulator's system) requires standardized APIs and identity federation, which a dynamic field of blockchain research.
Evolving Anomaly Patterns. As counterfeiters adapt, the LLM's detection capability may degrade.An online learning pipeline that feeds back verified anomalies (especially false negatives) for continuous prompt refinement or model fine-tuning would help maintain detection effectiveness.

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Conclusion

In order to secure the pharmaceutical supply chain, this paper introduced PharmGuard, a novel framework that combines permissioned blockchain technology with large language model analytics. The main technical contribution is the Provenance-Aware Anomaly Scoring (PAAS) mechanism, which detects a wide range of supply chain threats by combining LLM-based sequence anomaly scores with blockchain-derived provenance graph features.

PharmGuard works much better than five other systems, including the Anomaly Transformer (F1 = 0.872, $p < .001$ via McNemar's test), by testing it on 120,000 transactions with 600 fake anomalies. Its F1-score was 0.941 and its AUROC was 0.976. The ablation study demonstrated that the PAAS fusion yields a 9.2% enhancement in F1 score compared to independent LLM analysis, thereby substantiating the synergistic relationship between deterministic provenance verification and probabilistic pattern recognition. A formal threat model created detection guarantees for three types of enemies, one of which was the ability to find fake insertions from outside sources.

The outcomes show that blockchain and LLMs are complementary technologies: While LLMs offer intelligence without explicit programming, blockchain offers trust without a central authority. These advantages are combined by the PAAS mechanism to create a logical framework for anomaly detection that complies with EU FMD regulations and DSCSA. With 94% accuracy and high usability ratings from subject matter experts, the natural language query interface further democratizes access to blockchain-secured provenance data.

With the analysis of the practical deployment, it is demonstrated that PharmGuard is economically viable ($15,000–55,000/year) with multiple privacy-preserving deployment options including on-premise LLM hosting. The framework extends the generalization of pharmaceuticals to any provenance-critical supply chain.

Future research will concentrate on cross-chain interoperability, real-time streaming integration, adversarial robustness assessment, and pilot deployment with industry partners. In order to advance this promising strategy toward production-grade deployment and ultimately shield patients from the grave threat of subpar and counterfeit medications, we encourage interdisciplinary collaboration between supply chain specialists, AI researchers, and blockchain developers.

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