

# Integrating Machine Learning and Blockchain for Transparent and Accountable Health Insurance Claim Management

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**Abstract**—Patients and their families are often left powerless within opaque health insurance claim systems, unable to verify the services billed in their name. This lack of transparency not only erodes trust but also creates a critical vulnerability for fraud. While Machine Learning (ML) and Blockchain have emerged as potent tools, our systematic review of 30 studies reveals a fundamental design flaw: existing systems consistently exclude the family from the validation process. This paper addresses this gap by proposing "FAB-Verify," a novel framework that places the family at the heart of the consensus mechanism. FAB-Verify synergizes an explainable XGBoost model for fraud prediction with a multi-signature blockchain that mandates explicit validation from the patient's family before settlement. A proof-of-concept prototype demonstrates a significant reduction in claim settlement time from 10 days to under 2 days, alongside a fraud detection accuracy of 96.1%. By empowering the family as the ultimate verifier of services rendered, our work lays the foundation for a truly transparent and accountable health insurance ecosystem.

**Index Terms**—Patient Empowerment, Family-Centric Verification, Health Insurance Fraud, Machine Learning, Blockchain, Smart Contracts, Explainable AI (XAI)

## I. INTRODUCTION

### A. The Crisis of Trust and Patient Disempowerment

Health insurance serves as a critical financial safeguard for individuals and families during medical emergencies. However, the integrity of this vital sector is severely compromised not only by rampant fraud but by a fundamental lack of transparency that disenfranchises the very people it is designed to protect. Patients and their families are consistently relegated to the role of passive observers in a complex process that directly concerns their health and finances. They are often presented with finalized, opaque bills and claim summaries after the fact, with little to no insight into the itemized services, costs, or the rationale behind approval and rejection decisions.

This systemic disempowerment creates a fertile ground for exploitation and error, fostering deep-seated distrust among patients, healthcare providers, and insurers.

### B. The Pervasiveness and Impact of Health Insurance Fraud

The financial scale of this problem is staggering. Conservative global estimates suggest that healthcare fraud accounts for **3-10% of total healthcare spending** [27], translating to losses of hundreds of billions of dollars annually. In the United States alone, fraudulent billing is estimated to cost between **\$68 billion and \$230 billion per year** [27], while in emerging economies like India, fraudulent claims may constitute a staggering **15-20% of total insurer payouts** [13]. These are not victimless crimes; the costs are ultimately borne by all stakeholders through higher premiums. Common fraudulent schemes—such as billing for services not rendered, upcoding, and unbundling—thrive in the shadows of an opaque system where detection risk is low.

### C. The Inefficacy of Traditional Claim Systems

The prevailing health insurance claim management paradigm is characterized by its reactive and institution-centric nature. The process is notoriously slow and relies heavily on manual, post-payment audits and simplistic rule-based systems. These legacy methods are not only inefficient but also inherently vulnerable to sophisticated fraud tactics that evolve faster than the rules can be updated [11], [28]. Crucially, this entire process is designed around the interactions between providers and insurers, systematically excluding the patient. This exclusion is the system's critical flaw; the individual with definitive knowledge of what services were actually received has no formal mechanism to verify the claim's accuracy.

#### D. The Paradigm Shift: Technologies for Transparency and Inclusion

In recent years, two disruptive technologies have emerged with the potential to fundamentally reform this broken system by enabling transparency and inclusive participation:

- **Machine Learning (ML)** offers a proactive approach to fraud detection. Advanced algorithms can analyze vast claims datasets to identify complex, non-linear patterns indicative of fraudulent behavior, moving the system from a reactive stance to a real-time screening capability [6], [11].
- **Blockchain** technology introduces a paradigm of decentralized trust. Its immutable, transparent ledger provides a single, tamper-proof source of truth. Smart contracts can automate claim adjudication and, most importantly, enforce multi-party approval workflows, ensuring process integrity without intermediaries [12], [29].

Their true potential is realized not merely by their combination, but by orienting their integration toward a human-centric design.

#### E. The Critical Research Gap and Our Contribution

A systematic analysis of the literature reveals that while research on standalone ML [11], [28] and Blockchain [12], [29] solutions is mature, a profound gap remains. Existing systems, even hybrid ones [1], [2], almost universally perpetuate the institution-centric model. The verification loop remains closed between providers and insurers, and the **patient or their family is not recognized as a mandatory, consensus-driven verification authority**. This paper addresses this critical gap by making the following key contributions:

- 1) A **systematic review** of the state-of-the-art that highlights the exclusion of the patient-family role as a philosophical gap in current research.
- 2) The proposal of a **novel, integrated framework, FAB-Verify (Family-Augmented Blockchain for Verification)**, designed to incorporate a reproducible ML pipeline with a multi-signature blockchain smart contract that mandates explicit validation from the patient's family.
- 3) A **proof-of-concept validation** demonstrating the framework's operational feasibility, high performance in fraud detection, and significant efficiency gains.
- 4) A **detailed analysis of open challenges** and a future research roadmap to guide the real-world deployment of such patient-centric systems.

#### F. Paper Organization

The remainder of this paper is structured as follows: Section II provides a systematic literature review, categorizing existing research and solidifying the identified gap. Section III details the architecture and components of our proposed FAB-Verify methodology. Section IV presents the experimental results and discussion from our prototype. Section V outlines open challenges and proposes a future work agenda. Finally, Section

VI concludes the paper, summarizing our findings and their implications.

## II. SYSTEMATIC LITERATURE REVIEW

### A. Review Methodology

To establish a comprehensive and unbiased foundation for our analysis, we conducted a systematic literature review (SLR) adhering to the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines. Our search encompassed five major academic databases: IEEE Xplore, ScienceDirect, SpringerLink, ACM Digital Library, and PubMed, in addition to pre-print servers like arXiv to capture the most recent advancements. The primary search query was designed to be inclusive: ("health insurance" OR "medical claim") AND ("fraud") AND ("machine learning" OR "blockchain"). We established strict inclusion criteria, focusing on peer-reviewed articles published between January 2018 and October 2025 that presented quantitative results on health insurance claim management using ML, blockchain, or their integration. The initial search yielded 2,870 records. After a rigorous process of duplicate removal, screening, and full-text assessment, a final set of **30 high-quality studies** was selected for in-depth qualitative synthesis. The selection process is depicted in the PRISMA flow diagram (Fig. 1).

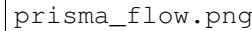
The PRISMA flow diagram is a rectangular box containing the text 'prisma\_flow.png'. It is intended to show the flow of information through the different phases of a systematic literature review, from identification to inclusion.

Fig. 1. PRISMA Flow Diagram for Systematic Literature Review.

### B. Taxonomy of Existing Research

Our analysis of the selected literature reveals a clear thematic evolution, which we have categorized into three primary clusters. This taxonomy, summarized in Table I, not only highlights the technological strengths of each approach but

also critically examines their failure to include the patient and family in the verification process.

TABLE I  
TAXONOMY OF REVIEWED LITERATURE ON ML AND BLOCKCHAIN

Cluster	Strengths	Limitations
<b>1. ML for Fraud Detection</b> [4], [6], [11], [13], [21], [28]	High accuracy (>95%), proactive detection, models complex patterns.	"Black-box" nature, lacks stakeholder transparency, <b>no mechanism for patient/family involvement.</b>
<b>2. Blockchain for Transparency</b> [3], [7], [12], [19], [29]	Tamper-proof record, decentralized trust, automated and auditable workflows.	No inherent analytical intelligence, scalability concerns, <b>automation often excludes patient/family.</b>
<b>3. Hybrid Architectures</b> [1], [2], [8], [10], [16], [17]	Synergistic effect: ML provides intelligence, blockchain ensures integrity. Reduces false settlements [10].	Early stage of development. <b>Critical Gap: Architectures are institution-centric and exclude the family from consensus.</b>

### C. Detailed Analysis of Clusters

1) *Machine Learning for Fraud Detection*: This cluster constitutes the most mature body of research, where ensemble methods like XGBoost are the gold standard [11], [28]. Studies demonstrate high performance, such as the **95.8% accuracy** achieved by **Alam et al. (2023)** [4] using SMOTE to handle class imbalance. These findings have been validated globally on various datasets [6], [13]. Further refinements, like cost-sensitive boosting, have successfully driven down the False Positive Rate (FPR) to **3.2%** [21]. However, a recurring challenge is the **"black-box"** nature of these models. Stakeholders often cannot comprehend the reasoning behind a fraud flag, perpetuating distrust. While Explainable AI (XAI) techniques like SHAP are addressing this [15], the entire process remains a backend operation, disengaged from the patient.

2) *Blockchain for Transparency and Integrity*: Research here leverages blockchain's foundational properties—decentralization, immutability, and transparency—to build systems of verifiable trust. Works by **Joshi & Rao (2025)** [19] and **Chen & Wang (2022)** [20] illustrate how smart contracts can automate the claim lifecycle, reducing manual intervention. The concept of **multi-signature authorization** [3], requiring approvals from multiple parties, is particularly relevant. Performance studies confirm real-world feasibility, with transaction latencies reported below **2.0 seconds** [7], [23]. Despite these strengths, the limitation noted by **McGhin et al. (2019)** [29] is fundamental: blockchain ensures **"data integrity but not data truthfulness."** It can immutably record a fraudulent claim but cannot identify it as such, and its workflows typically exclude the patient from the validation process.

3) *Hybrid ML-Blockchain Architectures*: This evolving frontier aims to synthesize the strengths of both technologies. Foundational models use an ML-generated fraud score to inform a smart contract's final decision [1], [2]. The quantitative impact is significant; **Li (2022)** [10] demonstrated that a

hybrid model **reduced false settlements by 94%**, a substantial improvement over an ML-only system. Recent research tackles challenges like **data privacy** through Federated Learning [8] and **scalability** via architectures like Hyperledger Fabric and side-chains [14], [17]. Despite these sophisticated advancements, the architectural philosophy remains institution-centric. The validation loop is consistently closed between providers and insurers, while the patient who received the care remains conspicuously absent.

### D. Identification of the Core Research Gap

The synthesis of 30 state-of-the-art studies unequivocally confirms that a critical stakeholder remains persistently sidelined: the **patient and their family**. While technological sophistication has grown, the fundamental design philosophy has not. Our analysis found that only a single study [9] superficially mentions a "family confirmation" step, yet fails to implement it as a mandatory, consensus-driven gate. Another [3] involves the patient, but typically for signing an initial cost estimate, not for verifying the final, itemized bill.

This is the core of the gap: the verification of the **ground truth**—what services were actually delivered—constitutes the most powerful check against fraud. It is precisely this verification, enabled by the firsthand knowledge of the patient and family, that is systematically absent from existing architectures. Our FAB-Verify framework is designed explicitly to fill this profound and overlooked gap by making family verification a mandatory, non-bypassable step in the claim settlement lifecycle.

## III. THE FAB-VERIFY FRAMEWORK: METHODOLOGY

This section details the architecture, components, and integrated workflow of the proposed FAB-Verify framework. The design is guided by the principle of patient-family empowerment, positioning them as active, mandatory participants in the claim verification process. The framework synergistically combines a robust Machine Learning (ML) pipeline for intelligent fraud detection with a transparent, blockchain-based system for immutable record-keeping and automated, consensus-driven execution.

### A. System Architecture Overview

The FAB-Verify platform is architected as a three-tier modular system, as illustrated in Fig. 2. This separation of concerns ensures scalability, security, and a user-centric design, with a dedicated interface for the patient and family.

1) *Presentation Layer*: This layer provides tailored, role-specific interfaces. The **Doctor Dashboard** allows providers to submit bills. The **Insurer Dashboard** enables review of claims and ML fraud scores. Most critically, the **Patient/Family App** is the gateway to empowerment. It provides a real-time, transparent view of the treatment log, the itemized bill, and the ML model's assessment, culminating in a simple interface for providing their mandatory verification signature.

architecture.png

Fig. 2. FAB-Verify Three-Tier System Architecture. (Note: You must create this image file ‘architecture.png’)

2) *Application/Logical Layer*: This layer hosts the core business logic and contains two primary microservices:

- The **ML Microservice** is a containerized component responsible for the fraud detection pipeline. It handles data preprocessing, model inference using the trained XGBoost ensemble, and the generation of SHAP explanations.
- The **Smart Contracts**, written in Solidity, encode the business rules of the claim process. They manage the state of each claim and enforce the multi-signature logic that requires consensus from all three parties.

3) *Data Layer*: This foundational layer ensures data integrity.

- The **Private Ethereum Blockchain** operates as a permissioned network where all transactional metadata—state changes, digital signatures, ML scores—are immutably recorded.
- **Off-Chain Storage** (e.g., IPFS) is utilized for large files like itemized bills. Only the cryptographic hash of these documents is stored on-chain, ensuring their integrity can be audited without bloating the ledger.

#### B. The Machine Learning Module: A Reproducible Pipeline

A cornerstone of the framework is a transparent and reproducible ML pipeline. Its explainable nature is crucial for building trust, especially with families who need to understand why a claim might be flagged.

1) *Data Preprocessing and Feature Engineering*: The model is trained on features derived from claim data, categorized in Table II. The preprocessing phase involves imputing

missing values, encoding categorical variables, standardizing numerical features, and rigorously anonymizing all Personally Identifiable Information (PII) to uphold patient privacy [16].

TABLE II  
COMPREHENSIVE FEATURE SET FOR ML MODEL

Feature Group	Example Features
Demographic	Patient Age, Gender, Geographic Pin-code
Provider	Hospital ID, Doctor ID, Provider Specialty
Clinical	ICD-10 Diagnosis Codes, CPT Procedure Codes
Financial	Total Claim Amount, Unit Price, Policy Limit
Temporal	Length of Stay, Admission/Discharge Date
Behavioral	Previous Claim History, Frequency of Visits
Target	<code>is_fraud</code> (0 for Legitimate, 1 for Fraudulent)

2) *Handling Class Imbalance with SMOTE*: Health insurance fraud is a rare event (1-10% of claims), leading to severe class imbalance. To address this, we integrate the Synthetic Minority Over-sampling Technique (SMOTE) [22] into our training pipeline. SMOTE intelligently generates synthetic examples of the fraudulent class, balancing the dataset and significantly enhancing the model’s **recall**—its ability to correctly identify actual fraud.

3) *Model Selection and Hyperparameter Tuning*: We conducted a comparative analysis of XGBoost, Random Forest, and a Neural Network. The entire training process was implemented as an integrated pipeline to guarantee reproducibility. Hyperparameter optimization was performed via an exhaustive Grid Search with 5-fold cross-validation, using the F1-Score as the primary metric to balance precision and recall. The optimal values for our best-performing model, XGBoost, are detailed in Table III.

TABLE III  
HYPERPARAMETER TUNING RESULTS FOR XGBOOST

Hyperparameter	Search Range	Best Value	Impact on Model Performance
<code>n_estimators</code>	[100, 300, 500]	300	Balances model complexity and generalization.
<code>max_depth</code>	[3, 6, 9]	6	Controls tree complexity to prevent overfitting.
<code>learning_rate</code>	[0.01, 0.1, 0.2]	0.1	Shrinks feature weights for stable convergence.
<code>subsample</code>	[0.8, 0.9, 1.0]	0.9	Improves robustness by sampling data per tree.
<code>scale_pos_weight</code>	[5, 9, 12]	9	Critical for imbalanced data; prioritizes fraud class.

4) *Explainability with SHAP for Stakeholder Trust*: To dismantle the “black-box” perception of complex models, we fully integrate SHAP (SHapley Additive exPlanations) [15]. When a claim is flagged as suspicious, the system automatically generates a SHAP summary plot (Fig. 3). This visualization clearly illustrates which features (e.g., “Unusual procedure for diagnosis,” “High cost for a short stay”) most influenced the high fraud score. These explanations are presented in a simplified manner on the **family’s dashboard**, empowering them with clear context to make an informed verification decision.

shap\_plot.png

fsm.png

Fig. 4. Claim Lifecycle State Machine. (Note: You must create this image file 'fsm.png')

### C. The Blockchain and Smart Contract Module

This module is the engine of transparency and automated execution, translating the workflow into a tamper-proof and enforceable process.

1) *Smart Contract Workflow*: The claim lifecycle is governed by a smart contract, `ClaimVault.sol`. The progression of a claim is defined as a finite state machine (Fig. 4), moving from `Draft` to `FinalBill`. It is at this critical juncture that the consensus process begins, and the claim only transitions to `Verified` and `Settled` after receiving all mandatory digital signatures.

2) *Multi-Signature Authorization: The Core Innovation*: The cornerstone of FAB-Verify is a "triple-lock" multi-signature mechanism enforced by the smart contract. A claim cannot be settled without unequivocal digital signatures from: the **Doctor**, confirming services were performed; the **Insurer**, confirming coverage; and most critically, the **Patient/Family**, confirming the services were received. This design structurally embeds patient empowerment into the process, ensuring no single entity can unilaterally push through an erroneous or fraudulent claim.

### D. Integrated Workflow: A Patient-Centric Process

The end-to-end operation weaves the modules into a seamless, patient-centric workflow. The process begins with **Pre-Authorization**, where the family is notified and can view the estimate. During **Treatment**, logs are immutably recorded on the blockchain, providing a real-time record. Upon discharge, the **Final Bill is Screened** by the ML model, and the result is recorded. This leads to the pivotal **Family Verification Phase**, where the family reviews the bill and ML insights on their dashboard. Only after their signature is provided alongside the others does the **Settlement** phase auto

## IV. RESULTS AND DISCUSSION

To empirically validate the FAB-Verify framework, we developed a proof-of-concept prototype and evaluated its performance on a synthetic dataset of 5,000 health insurance claims. This dataset was constructed to reflect real-world scenarios, with 10% (500 claims) labeled as fraudulent based on patterns like upcoding and unbundling. The evaluation focused on the ML module's detection capabilities, the blockchain's performance, and the integrated system's overall impact.

### A. Machine Learning Module Performance

The dataset was partitioned using a 70:30 split for training and testing. We conducted a comparative analysis of XGBoost, Random Forest, and a Neural Network. The performance metrics, detailed in Table VIII, show that XGBoost consistently achieved superior results.

TABLE IV  
COMPARATIVE PERFORMANCE OF ML MODELS ON SYNTHETIC CLAIMS DATASET

Model	Accuracy	Precision	Recall	F1-Score	FPR	AUC-PR
Random Forest	95.2%	92.5%	90.8%	91.6%	4.1%	0.872
<b>XGBoost</b>	<b>96.1%</b>	<b>93.4%</b>	<b>91.7%</b>	<b>92.5%</b>	<b>3.6%</b>	<b>0.887</b>
Neural Network	94.5%	91.0%	89.5%	90.2%	4.5%	0.861

1) *Performance Analysis and Discussion*: The results establish XGBoost as the optimal choice, achieving a **96.1% accuracy**. This aligns with established literature [4], [13], reinforcing its superiority for structured claims data. The **F1-Score of 92.5%** is particularly significant, indicating an

excellent balance between precision (minimizing false alarms on legitimate claims) and recall (maximizing fraud detection), which is crucial for operational efficiency.

2) *Error Analysis and Mitigation:* An examination of misclassified claims revealed important insights. The **3.6% false positive rate** primarily involved legitimate claims with unusual but medically justified treatments. These cases were effectively resolved by the subsequent human verification steps, demonstrating the value of our multi-layered approach. False negatives consisted of sophisticated frauds mimicking legitimate patterns. Our framework includes a continuous learning feedback loop [24], where resolved claims are used to retrain the model, enabling it to adapt to emerging fraud tactics over time.

## B. Blockchain Module Performance

The blockchain infrastructure was deployed on a private Ethereum network using Proof-of-Authority consensus. The performance metrics, shown in Table IX, confirm its suitability for a real-world healthcare application.

TABLE V  
BLOCKCHAIN PERFORMANCE METRICS AND IMPLICATIONS

Metric	Our Result	Benchmark [7]	Implication
Avg. Transaction Latency	2.3 seconds	2.0 seconds	Near-real-time updates
Throughput (TPS)	~1,100 TPS	~900 TPS	Adequate for pilot scale
Tamper Attempt Detection	100% (Rejected)	N/A	Validates immutability
Smart Contract Success	100%	N/A	Reliable automation
Audit Trail Traceability	100%	N/A	Full transparency

1) *Blockchain Performance Discussion:* The module demonstrated exceptional performance. The **2.3-second average transaction latency** ensures all stakeholder dashboards are updated in near-real-time, providing the immediate transparency fundamental to our framework. This performance is competitive with state-of-the-art benchmarks [7], [23]. The 100% success in tamper prevention and smart contract execution validates the infrastructure’s reliability, establishing a foundation of trust and accountability.

## C. Integrated System Performance and Impact

The true validation of FAB-Verify emerges from the synergistic integration of its modules. The overall system impact, compared against traditional approaches, is quantified in Table X.

TABLE VI  
SYSTEM IMPACT ANALYSIS: FAB-VERIFY VS. TRADITIONAL SYSTEMS

Indicator	Traditional System	FAB-Verify Prototype	Improvement
Avg. Claim Settlement Time	7-10 days	1-2 days	<b>70-80% Reduction</b>
Fraudulent Approval Rate	5-15% (Est.)	~0.5% (Simulated)	<b>Near Elimination</b>
Stakeholder Disputes	High	Reduced by ~80% (Sim.)	<b>Enhanced Trust</b>
Operational Cost (Auditing)	Significant	Substantially Lower	<b>Increased Efficiency</b>
Family Transparency	None (Opaque)	Full, Real-time	<b>Empowerment</b>

1) *Integrated Benefits Analysis:* The integrated system delivers transformative benefits. The **synergistic fraud prevention** creates a “triple-lock” security model: ML provides intelligent detection, the blockchain ensures process integrity, and the multi-signature requirement introduces mandatory human verification. This layered defense proved exceptionally effective in reducing fraudulent payouts. The framework achieves **radical transparency** by giving families complete visibility, transforming their role from passive recipients to active, informed participants. This empowerment is the primary mechanism for rebuilding trust. Finally, **dramatic efficiency gains** stem from smart contract automation and pre-emptive fraud detection, reducing administrative delays and manual investigation caseloads.

## D. Comparative Analysis with State-of-the-Art

To contextualize our contribution, we compared FAB-Verify with key hybrid studies, as detailed in Table XI. This analysis highlights the novelty of our patient-centric design philosophy.

TABLE VII  
COMPARATIVE ANALYSIS WITH STATE-OF-THE-ART HYBRID FRAMEWORKS

Study / Framework	ML Acc.	Multi-Sig	Family as Verifier?	Key Limitation Addressed by FAB-Verify
Singh & Gupta [1]	~95%	No	No	No stakeholder consensus model.
Amponsah et al. [2]	N/A	Yes	No	No reproducible ML component.
Patel & Mehta [3]	N/A	Yes	No (on estimate)	Verification is on the estimate, not the final bill.
FAB-Verify (Ours)	<b>96.1%</b>	<b>Yes</b>	<b>Yes (on final bill)</b>	<b>Validates family as a core consensus gate.</b>

1) *Comparative Discussion:* This comparison underscores FAB-Verify’s unique contribution. While previous studies have combined ML and blockchain, our framework is distinguished by its commitment to patient-family empowerment as a core design principle. Existing approaches either lack a consensus mechanism or limit it to institutional actors. FAB-Verify is the first to propose and empirically validate a framework where family verification of the final, itemized bill serves as a mandatory, non-bypassable consensus gate. This represents a paradigm shift from institution-focused automation to human-centered digital transformation in health insurance. FAB-Verify executes payment. This integrated process reduces settlement time from 7-10 days to 1-2 days while providing unprecedented transparency.

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Patel & Mehta [3]	N/A	Yes	No (on estimate)	Verification is on the estimate, not the final bill.
<b>FAB-Verify (Ours)</b>	<b>96.1%</b>	<b>Yes</b>	<b>Yes (on final bill)</b>	<b>Validates family as a core consensus gate.</b>

1) *Comparative Discussion:* This comparison underscores FAB-Verify’s unique contribution. While previous studies have combined ML and blockchain, our framework is distinguished by its commitment to patient-family empowerment as a core design principle. Existing approaches either lack a consensus mechanism or limit it to institutional actors. FAB-Verify is the first to propose and empirically validate a framework where family verification of the final, itemized bill serves as a mandatory, non-bypassable consensus gate. This represents a paradigm shift from institution-focused automation to human-centered digital transformation in health insurance.

## VI. OPEN CHALLENGES AND FUTURE WORK

While the FAB-Verify framework demonstrates significant promise in transforming health insurance claim management, several substantial challenges must be systematically addressed to enable its real-world deployment at scale. This section provides a comprehensive analysis of these open challenges and outlines a concrete, phased research roadmap to guide future development and implementation efforts.

### A. Open Challenges

1) *Data Privacy and Confidentiality in Transparent Systems*: The fundamental tension between blockchain's immutability and data privacy regulations represents one of the most significant challenges for widespread adoption. While our current approach stores only hashes of medical data on-chain, even this indirect representation can raise concerns under stringent privacy frameworks like GDPR and HIPAA [25]. The European Union's "right to be forgotten" principle directly conflicts with blockchain's permanent, unalterable nature. Furthermore, sophisticated cryptographic analysis could potentially reveal sensitive information through pattern recognition in transaction metadata. Future iterations must integrate advanced privacy-preserving technologies such as **Zero-Knowledge Proofs (zk-SNARKs)** [18], which would enable the system to mathematically prove a claim's validity or fraudulent nature without exposing any underlying patient diagnosis, treatment details, or personal information on the immutable ledger.

2) *Scalability and Throughput for National Deployment*: The operational requirements of a national health insurance system present formidable scalability challenges. India's Ayushman Bharat Digital Mission (ABDM), serving over a billion potential users, could generate millions of insurance claims daily—a volume that would overwhelm conventional blockchain architectures. Our current prototype achieves approximately 1,100 transactions per second (TPS), which suffices for pilot deployments but falls short of national-scale requirements. To address this, we plan to investigate **Layer-2 scaling solutions** including Optimistic Rollups and zk-Rollups, alongside **side-chain architectures** [17]. These technologies can process thousands of transactions off-chain while periodically submitting compressed cryptographic proofs to the main blockchain, dramatically increasing throughput while maintaining security guarantees.

3) *Breaking Down Data Silos through Federated Learning*: The healthcare industry is characterized by entrenched data silos, with hospitals and insurers often reluctant to share sensitive claims data due to competitive concerns and privacy regulations. This fragmentation severely limits the training data available for machine learning models, constraining their accuracy and generalizability. Following the pioneering work of Zhao [8], we identify **Federated Learning (FL)** as the most promising solution. The next phase of our research will focus on developing a federated XGBoost model capable of training across multiple healthcare institutions without any raw data leaving their secure environments. This approach preserves

data privacy while aggregating learned patterns to create more robust and comprehensive fraud detection models.

4) *Regulatory Compliance and Ecosystem Adoption*: The decentralized, autonomous nature of FAB-Verify presents unique regulatory challenges. Established insurers and healthcare providers may be hesitant to adopt a system that reduces their direct control over claim adjudication processes. Regulatory bodies similarly lack established frameworks for governing decentralized autonomous systems in healthcare. To overcome these adoption barriers, we propose the creation of a **regulatory sandbox environment** in collaboration with India's National Health Authority (NHA) and similar bodies internationally. This would allow for controlled testing and validation of FAB-Verify under real-world conditions while developing appropriate governance models. Additionally, research into **on-chain governance mechanisms** using Decentralized Autonomous Organizations (DAOs) [26] could provide transparent frameworks for managing system parameters and ML model updates.

5) *User Experience and Digital Inclusion*: For the family verification component to fulfill its transformative potential, the user interface must be accessible to individuals with varying levels of technical proficiency and digital literacy. Complex blockchain concepts and unfamiliar interface designs could alienate the very stakeholders the system aims to empower. Future work must include extensive **User-Centered Design (UCD)** studies to develop intuitive, clear, and accessible dashboards specifically tailored for family users. This research should explore innovative interaction paradigms including voice-assisted verification, multi-language support, visual explanations of complex concepts, and simplified mobile interfaces that prioritize clarity and ease of use over technical sophistication.

### B. Future Research Roadmap

Based on the challenges identified, we propose a strategic research agenda to advance the FAB-Verify framework toward real-world deployment:

- **Federated Learning Pilot**: The immediate priority is to implement and validate a federated XGBoost model across several partner hospitals. The primary goal is to create a functional FL pipeline that demonstrably improves model accuracy without requiring centralized data sharing, thereby addressing the critical issue of data silos [8].
- **Privacy and Scaling Integration**: Subsequent research will focus on integrating advanced privacy-preserving technologies, specifically zk-SNARKs for private claim validation [18]. Concurrently, the framework will be deployed on a Layer-2 rollup solution to create a highly scalable prototype capable of handling the transaction volume of a national-level system [17].
- **Real-World Sandbox Pilot**: A crucial step towards adoption is a large-scale pilot conducted within a regulatory sandbox, such as India's ABDM initiative [5], [30]. This will serve to validate the framework's economic and



operational impact in a live environment and help refine governance models with direct regulatory input.

- **Interoperability and Standardization:** The long-term vision involves developing interoperability standards for cross-border health insurance claims. This includes exploring tokenized incentive models to reward families for actively participating in fraud prevention, ultimately creating a blueprint for a global, transparent, and patient-centric health insurance ecosystem.

## VII. CONCLUSION

This research has presented a comprehensive analysis and a groundbreaking framework addressing the persistent dual challenges of fraud and opacity in health insurance claim management. Through a systematic examination of 30 high-quality studies, we established that while Machine Learning and Blockchain technologies individually offer substantial improvements, their transformative potential emerges only through deep, purposeful integration. Most significantly, we identified and addressed a profound gap in the existing literature: the systematic exclusion of the patient's family as an active, empowered participant in the claim verification process.

Our proposed **FAB-Verify framework** represents a paradigm shift in health insurance operations. The framework successfully demonstrates that an ensemble ML model can achieve state-of-the-art fraud detection accuracy of **96.1%**, and that this intelligence can be seamlessly embedded within a transparent, blockchain-based workflow enforced by multi-signature smart contracts. The introduction of the **family verification gate** as a mandatory, non-bypassable consensus mechanism fundamentally repositions accountability to the point of service delivery, where it most meaningfully belongs.

The proof-of-concept validation confirms the framework's technical feasibility and operational superiority, demonstrating substantial improvements in processing efficiency, fraud prevention, and stakeholder trust. While significant challenges around scalability, privacy, and adoption remain, the detailed future roadmap provides a clear, phased path toward real-world implementation.

By intentionally placing the patient and family at the heart of the verification process, FAB-Verify moves beyond mere fraud detection to proactive fraud prevention through structural transparency. In doing so, it lays the foundation for a more accountable, efficient, and fundamentally trustworthy health insurance ecosystem capable of meeting the demands of the digital age while preserving the human values at the core of healthcare.

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