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A Quantum-Resistant Federated Blockchain Framework For Secure Multi-Institutional Healthcare Data Sharing And Clinical Decision Automation

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Abstract

The increasing demand for security and privacy-preserving collaboration among healthcare institutions presents significant challenges in data sharing, consent enforcement, and diagnostic automation, especially considering emerging quantum threats. This paper introduces PQ-FedCare, an innovative federated system architecture that incorporates post-quantum cryptography, zero-knowledge proofs, and smart contract–governed diagnostics to facilitate verifiable and privacy-compliant clinical collaboration. The proposed framework supports decentralized identity validation, encrypted consent delegation, and encrypted rule execution across blockchain-connected healthcare nodes. Using CRYSTALS-Kyber and SPHINCS+ for quantum-resistant security and zk-SNARKs for proof generation, PQ-FedCare ensures zero data exposure while enabling real-time, cross-institutional medical decision support. Evaluation on real-world clinical datasets (MIMIC-III, TCGA, and GEO GSE12102) demonstrates superior performance over recent baselines in diagnostic accuracy (94.5%), privacy leakage (0%), and proof verification time (92 ms). Additional stress tests confirm the system's robustness against missing data and scalability across federated nodes. The findings establish PQ-FedCare as a forward-compatible infrastructure for secure, accountable, and future-proof federated healthcare diagnostics. The proposed work is particularly suited for high-stakes clinical environments demanding transparency, regulatory compliance, and resistance to quantum-era attacks.

Keywords: *Blockchain, Consent Management, Federated Learning, Post-Quantum Cryptography, Smart Contracts, Zero-Knowledge Proofs*

1. INTRODUCTION

In recent years, healthcare systems worldwide have embraced digital transformation by integrating cloud computing and artificial intelligence to manage electronic health records, diagnostic imaging, treatment plans, and patient monitoring. These innovations have enhanced the efficiency and accessibility of medical services, yet they have also introduced new risks related to the confidentiality, integrity, and availability of sensitive patient data. The growing volume of healthcare data, combined with strict regulatory requirements such as HIPAA and GDPR, demands secure, scalable frameworks for managing medical information across distributed cloud environments. Compounding this challenge, the emergence of quantum computing poses a significant threat to traditional encryption methods, risking long-term data confidentiality. In response to these concerns, the QP-ChainSZKP framework was previously proposed to secure single-institution healthcare cloud systems using post-quantum cryptography, zero-knowledge proofs, and blockchain-backed validation. While effective in isolated deployments, this model does not support collaborative healthcare scenarios that involve multiple stakeholders.

To support secure, real-time collaboration among hospitals, labs, research centers, and insurers, QP-ChainSZKP is being extended into a federated, quantum-resilient system. Timely access to shared medical

records and diagnostic intelligence is crucial for high-impact scenarios like rare disease analysis, cross-border clinical trials, and cancer diagnostics. However, the lack of mutual trust, insufficient policy enforcement, and absence of a federated privacy model continue to impede such efforts. Traditional encryption techniques and centralized access control systems fall short in addressing these interoperability and security challenges. There remains an unmet need for a decentralized, privacy-preserving framework that enables cross-institutional data exchange with cryptographic auditability and compliance-aware consent management.

This paper addresses the critical problem of enabling secure, federated, and quantum-resistant healthcare data sharing and clinical automation. Specifically, the problem lies in the lack of a comprehensive framework that can simultaneously ensure the privacy of medical data, manage decentralized access control, support regulatory compliance across jurisdictions, and withstand the computational threats posed by quantum computing. Existing systems either focus on centralized models or do not incorporate advanced cryptographic constructs that are secure against quantum adversaries. In environments where patient data is fragmented across various silos and where institutions must collaborate without compromising confidentiality or regulatory obligations, there is a dire need for a new architectural paradigm. This paradigm must not only extend the security guarantees of the original QP-ChainSZKP system but also provide the capabilities required for real-time, rule-based decision support and cross-institutional data validation.

This research aims to create PQ-FedCare, a new federated framework for secure, quantum-resistant, and scalable data exchange among healthcare providers. The framework introduces post-quantum threshold cryptography to support distributed key management and consensus, federated zero-knowledge proofs for privacy-preserving authentication and transaction validation, and blockchain-backed smart contract engines that automate clinical rule enforcement. PQ-FedCare also integrates a quantum-resistant data provenance mechanism that ensures the traceability and integrity of health data transactions across organizational boundaries. The system is designed to simulate realistic multi-institutional scenarios where medical data must be shared under strict access control, and where decision-making must occur without compromising patient privacy or institutional autonomy. The framework is evaluated on its ability to maintain low latency, high throughput, secure identity management, and seamless compliance with healthcare regulations.

The significance of this work lies in its potential to reshape how healthcare institutions collaborate. By offering a federated, decentralized alternative to traditional siloed data systems, PQ-FedCare empowers hospitals, diagnostic labs, and healthcare regulators to interact securely and transparently without relying on centralized intermediaries. The integration of quantum-secure techniques ensures that the proposed system remains relevant and resilient even in the face of future quantum-enabled attacks. Furthermore, the incorporation of a clinical rule engine that operates over encrypted data allows real-time medical decisions to be made with minimal human intervention, thereby reducing diagnostic errors and improving patient outcomes. This innovation closes the privacy-utility gap in healthcare digitization. Using blockchain and post-quantum technologies, PQ-FedCare sets a new standard for private and scalable eHealth systems.

This paper is organized as follows. The following section provides an extensive review of existing work on blockchain in healthcare, zero-knowledge proofs, and post-quantum cryptographic frameworks, highlighting the limitations of current systems and the gaps in research that this paper seeks to fill. The third section revisits the architectural design and limitations of QP-ChainSZKP, explaining how PQ-FedCare expands upon this foundation. Experimental setup and results are then discussed, demonstrating the system's performance under varying network and load conditions. It provides an in-depth discussion on the implications of the results, in comparison with existing frameworks. This paper concludes with conclusions and future research directions.

2. LITERATURE REVIEW

As data-driven diagnostics and personalized treatments become mainstream, the need for secure and privacy-preserving healthcare data sharing frameworks has intensified. Traditional centralized models are increasingly insufficient due to risks related to data breaches, regulatory non-compliance, and lack of transparency. Numerous recent works have proposed federated and blockchain-based alternatives, yet gaps remain in

integrating quantum-resistant security, dynamic consent enforcement, and zero-knowledge verification. This review synthesizes prior contributions to identify research directions that inform the design of PQ-FedCare.

Jain et al. (2024) introduced a blockchain-based architecture combining CRYSTALS-Kyber and SPHINCS+ for quantum-resistant encryption. Their system safeguards electronic medical records and ensures decentralized access control, though future-proofing the cryptography remains a concern. Jin et al. (2020) developed a blockchain-based model using broadcast encryption and key regression to manage access to medical datasets. While it preserves privacy across geo-scattered systems, it lacks quantum resilience and real-time policy enforcement.

Sági and Molnár (2023) examined challenges in federated personalized medicine, highlighting friction between clinical and molecular data silos. Though the study emphasizes regulatory alignment, it does not offer cryptographic safeguards or automated compliance tools. Firdaus and Rhee (2023) proposed a blockchain-enhanced federated learning system (CSFL-BDP) to facilitate cross-silo healthcare training. It strengthens trust and model auditability, but its reliance on classical cryptography introduces vulnerabilities in the post-quantum era.

Selvi and Thamilselvan (2022) combined federated learning and differential privacy over a blockchain layer to mitigate centralized failure risks. However, it lacks decentralized consent enforcement and uses static access policies. Liu et al. (2022) enhanced federated learning with smart contracts for secure health data sharing but did not support dynamic delegation or fine-grained proof-based access verification.

Ahmed et al. (2021) proposed a blockchain-AI hybrid for managing medical data securely. Their model integrates AI-driven insights with ledger-based auditability but does not address identity privacy or inter-institutional trust delegation. Luo et al. (2022) incorporated federated learning with blockchain support for diagnosis modeling, offering model traceability but no native zero-knowledge or post-quantum security features.

Zhang et al. (2023) were among the few to emphasize post-quantum blockchain, applying lattice cryptography to secure medical records. Yet, the system lacks dynamic interoperability with existing federated learning tools. Kumar et al. (2021) designed smart contract-based consent mechanisms to govern access to healthcare records. Their model improves patient autonomy but does not integrate verifiable credentials or proof-of-access structures.

Wei et al. (2020) incorporated zero-knowledge proofs with blockchain for privacy-preserving medical data sharing. Their approach ensures verification without disclosure but is limited to static credential schemes. Farouk et al. (2022) proposed a federated blockchain framework for electronic health records that decentralizes control but does not address secure collaborative analytics or cross-institutional rule enforcement.

Prakash and Sivanandam (2021) presented a decentralized AI framework for preserving privacy in clinical decision-making. However, their system does not feature immutable auditability or consent tracking. Ayadi et al. (2020) offered a privacy-preserving architecture for medical blockchain applications, focusing on data anonymization rather than cryptographic validation.

Gao et al. (2023) introduced a zero-knowledge proof-based access control model in federated healthcare. Their protocol supports privacy-preserving validation of credentials, aligning closely with PQ-FedCare's philosophy. Wang et al. (2022) proposed a lattice-based approach for genomic data sharing, enabling post-quantum security guarantees. While cryptographically robust, their focus remains narrow on genomic datasets.

Finally, Alhassan et al. (2021) combined federated learning and blockchain for pandemic surveillance. Their design enables distributed intelligence during health crises, but lacks mechanisms for consent, zero-knowledge delegation, or post-quantum readiness.

Collectively, these works show significant progress toward secure and interoperable healthcare systems. However, only a few combines post-quantum encryption with federated learning and zero-knowledge proofs. Fewer still support smart contract–enforced patient consent, cross-node rule evaluation, and cryptographic auditability. PQ-FedCare addresses these limitations by integrating Federated Post-Quantum Cryptography (FPQC), RuleZK smart contracts, and the PQ-Fed-ZKP protocol within a single interoperable architecture.

3. PQ-FedCare Architecture

3.1 Federated System Architecture

3.1.1 Overview of Federated Health Infrastructure

The PQ-FedCare framework is designed around a federated architecture model that supports distributed yet coordinated security among various healthcare entities. These entities include hospitals, diagnostic laboratories, pharmaceutical research centers, insurance providers, and governmental healthcare agencies. Unlike centralized systems, which rely on a singular point of control and data storage, the federated model enables each participant to maintain ownership and control over its own data while participating in a shared, secure ecosystem. This model is especially crucial in healthcare, where legal jurisdictions, institutional policies, and data sensitivity levels often differ significantly across organizations. The architecture is built to support interoperability without compromising data locality, compliance, or institutional autonomy.

Each participant in the federated network operates as an independent node that adheres to a common security protocol enabled by post-quantum cryptography (PQC) and privacy-preserving identity verification via zero-knowledge proofs (ZKPs). All nodes are connected through a permissioned blockchain layer, which functions as the consensus and logging mechanism for cross-organization transactions. This ensures that all actions taken within the network—such as data access, diagnostic rule validation, or consent management—are immutably recorded and can be independently audited. The design mitigates the risk of single points of failure while fostering a trustless environment where cooperation does not necessitate full disclosure or unconditional trust.

3.1.2 Post-Quantum Security Layer

The post-quantum security layer in PQ-FedCare is architected to address the imminent threat posed by quantum computing to classical cryptographic primitives. With the healthcare sector increasingly relying on digitally shared records, smart contract execution, and multi-institutional data collaborations, the transition to post-quantum security is critical. PQ-FedCare integrates two well-established, NIST-endorsed post-quantum cryptographic techniques: CRYSTALS-Kyber for encryption and SPHINCS+ for digital signatures. These methods are selected for their quantum resilience, computational efficiency, and compatibility with federated, privacy-critical infrastructures.

CRYSTALS-Kyber is employed for secure key encapsulation and inter-node communication due to its basis in the Learning With Errors (LWE) problem, which is known to be resistant to attacks from quantum algorithms such as Shor's. Unlike RSA or ECC, Kyber uses matrix and vector operations over polynomial rings, producing compact keys and ciphertexts while offering strong security guarantees. In the PQ-FedCare framework, Kyber is implemented in a distributed key generation setup, where each hospital or laboratory node generates a local key share. The collective session key used for communication is derived by XOR-ing these individual shares, formalized as $K = k_1 \oplus k_2 \oplus \cdots \oplus k_n$. This threshold mechanism prevents any single institution from gaining unilateral control over encryption keys, enforcing decentralized trust. The encapsulation process involves generating a ciphertext c_i and a shared secret k_i using the node's public key pk_i, while decapsulation retrieves k_i from the ciphertext using the secret key sk_i, i.e., $(c_i, k_i) \leftarrow \text{Encap}(pk_i)$ and $k_i \leftarrow \text{Decap}(sk_i, c_i)$.

This distributed key model is especially significant in the healthcare domain where data access, encryption, and decision-making must be both collaborative and auditable. The multi-party computation (MPC) context in which these operations are embedded ensures that cryptographic workflows—such as diagnosis submission, consent evaluation, and data decryption—are only executable when multiple authorized institutions participate, thereby minimizing insider threat vectors and enhancing inter-organizational accountability.

To ensure the authenticity of blockchain-stored transactions, diagnostic logs, and consent records, PQ-FedCare utilizes SPHINCS+, a stateless hash-based digital signature scheme that offers post-quantum resilience without relying on structured mathematical assumptions. SPHINCS+ is built solely on hash functions, which remain robust against Grover's algorithm, thus ensuring that signature forgery remains computationally infeasible even for quantum adversaries. Statelessness eliminates the need for synchronized

state tracking across federated nodes, reducing operational complexity and removing the risks associated with nonce reuse.

In PQ-FedCare, each transaction T is signed using a SPHINCS+ signing key sk to produce a signature σ, and any institution or auditor can later verify the signature using the corresponding public key pk through $\sigma \leftarrow \text{Sign}_{\text{SPHINCS+}}(sk, H(T))$ and $\text{Verify}_{\text{SPHINCS+}}(pk, H(T), \sigma) = 1$. These digital signatures are embedded into the blockchain ledger to provide long-term verifiability of all critical actions, including diagnosis confirmations, consent grants, and provenance assertions. The use of hash-based techniques also means that the system remains secure against potential advances in quantum hardware or cryptanalysis, providing durable protection for archival healthcare data.

Once the shared key K is generated using Kyber, PQ-FedCare establishes secure communication channels using symmetric authenticated encryption. This is essential for encrypting large volumes of data, such as medical images, diagnostic rules, or provenance logs, which are impractical to handle with asymmetric schemes. The chosen ciphers are AES-GCM and ChaCha20-Poly1305, which offer high performance, low latency, and built-in authentication, ensuring that encrypted messages cannot be forged or altered during transmission. These ciphers are initialized using the post-quantum derived session key K, ensuring that even if an attacker intercepts communication, no quantum algorithm can decrypt the contents or tamper with them retroactively.

This layered approach—Kyber for threshold key agreement, SPHINCS+ for tamper-proof signatures, and symmetric authenticated encryption for data transmission—creates a robust cryptographic foundation for the PQ-FedCare framework. It protects both data-in-transit and data-at-rest, provides decentralized control over access rights, and ensures immutable accountability for every transaction. By integrating only those cryptographic primitives that are vetted under the NIST post-quantum process and aligning them with federated operational constraints, PQ-FedCare establishes a forward-compatible security backbone that can withstand the emergence of quantum computing without compromising on interoperability, compliance, or clinical agility.

3.1.3 Federated Identity and Consent Model

In PQ-FedCare, the challenge of enabling secure and privacy-preserving access to sensitive medical data across independently governed healthcare institutions is addressed through a decentralized identity and consent model. This model is grounded in Decentralized Identifiers (DIDs) and Verifiable Credentials (VCs), compliant with the W3C standards. The architecture ensures that patient and clinician identities are cryptographically represented and validated without reliance on centralized identity providers or exposure of sensitive attributes. This is especially critical in federated healthcare environments, where participants belong to diverse administrative domains and are governed by distinct access control policies.

Each participant—whether a patient, clinician, researcher, or institutional node—is assigned a DID, which is a unique, persistent, and resolvable identifier rooted on the blockchain. The corresponding verifiable credentials are issued by trusted authorities such as hospitals, medical boards, or insurance providers. These credentials include claims such as professional affiliation, authorization scopes, or data ownership rights, and are signed using SPHINCS+ post-quantum digital signatures. The verification of these credentials is conducted using zero-knowledge proofs (ZKPs), which allow the bearer to prove the possession of certain attributes without revealing the attributes themselves. For example, a clinician can prove authorization to access oncology records without disclosing identity, role, or department explicitly.

Let $\mathcal{C}$ denote a verifiable credential, and π represent a zero-knowledge proof. A participant can generate a proof of valid credential possession as:

$$\pi \leftarrow \text{Prove}(\mathcal{S}, x, w)$$

where $\mathcal{S}$ is the statement to be proven (e.g., "Doctor X has access to oncology records"), x is the public component of the claim, and w is the witness (i.e., the secret credential). The verification is performed by another node using:

$$\text{Verify}(\mathcal{S}, x, \pi) = 1$$

This process ensures that no identifiable information is exposed during credential verification, fulfilling both HIPAA and GDPR mandates for data minimization and privacy by design.

To complement the federated identity system, PQ-FedCare introduces a decentralized consent management protocol, governed by smart contracts on the blockchain. Unlike traditional systems where patient consent is stored and enforced centrally, this approach allows patients to issue cryptographic consent tokens, encoding specific policies regarding data access scope, validity duration, recipient constraints, and contextual purposes. These tokens are generated locally and stored immutably on the blockchain ledger, forming auditable and enforceable commitments. Formally, a consent policy is modeled as a tuple:

$$\mathcal{P} = (t_{start}, t_{end}, R, S, \Pi)$$

where t_{start} and t_{end} define the time interval of consent validity, R is the resource or data asset being accessed, S is the subject (e.g., requesting institution), and Π is the permitted purpose or role. The policy enforcement engine evaluates incoming access requests using:

$$\delta(u, R, \mathcal{P}) = \begin{cases} 1 & \text{if } u \in S \text{ and current\_time} \in [t_{start}, t_{end}] \text{and purpose}(u) \in \\ 0 & \text{otherwise} \end{cases}$$

Here, u denotes the user or node initiating the request, and the function δ outputs whether access should be granted (1) or denied (0). This decentralized function is implemented within smart contracts that are triggered each time a data access transaction is submitted to the blockchain.

The use of smart contracts for consent enforcement ensures that every request is evaluated in a deterministic, transparent, and tamper-proof manner. Moreover, by storing consent policies on-chain with hash-based signatures, patients retain control over their data without requiring real-time interaction or re-authorization for every transaction. This model also supports revocation; a patient may update or invalidate an existing policy by broadcasting a new policy token with updated parameters and a higher version counter, which is automatically recognized by the smart contract validator.

By combining verifiable credentials with zero-knowledge validation and smart-contract governed consent enforcement, the PQ-FedCare framework provides a scalable, interoperable, regulation-compliant identity and access management system. This approach decentralizes control, preserves user anonymity, and provides mathematically verifiable accountability across the entire federated healthcare network.

Algorithm: PQ-Fed-ZKP Protocol

Input:

- Statement $\mathcal{S}$
- Public input x
- Private witness w
- Access policy ρ

Output:

- Authorization decision $\in \{0, 1\}$
- Blockchain log entry

```
1. π ← Prove(S, x, w)
2. result ← Verify(S, x, π)
3. if result == 1 and PolicySatisfied(ρ, x):
      GrantAccess()
      Log(H(S), x, π, timestamp) to Blockchain
   else:
      DenyAccess()
      Log(H(S), x, "denied", timestamp) to Blockchain
4. return result
```

3.1.4 Blockchain-Backed Rule Engine

A core innovation of the PQ-FedCare framework lies in its integration of a blockchain-backed clinical rule engine designed to automate, verify, and secure diagnosis and treatment validation workflows across federated healthcare institutions. In this architecture, diagnostic decision-support logic is encoded as smart contracts,

deployed onto a permissioned blockchain. These smart contracts embed formal medical rules contributed by participating hospitals, ensuring uniform clinical governance while maintaining institutional autonomy. To protect patient privacy during execution, the system relies on zero-knowledge proofs (ZKPs) and homomorphic encryption (HE), enabling rules to be applied to encrypted inputs without exposing sensitive clinical information.

Each clinical rule is defined as a computational predicate over patient attributes. Let x denote the encrypted input vector representing patient features (e.g., biomarkers, imaging-derived scores), and let R denote the diagnostic rule encoded as a function. The rule engine evaluates whether $R(x)$ returns a specific label or recommendation. To protect x, the system uses Fully Homomorphic Encryption (FHE), which supports computation directly on encrypted values. For a rule R, the encrypted evaluation is performed as:

$$\text{Enc}(y) = R_{\text{hom}}\big(\text{Enc}(x)\big)$$

where $\text{Enc}(x)$ is the ciphertext of the patient input, and R_{hom} represents the homomorphic version of the rule function. The output $\text{Enc}(y)$ can later be decrypted only by the data owner, preserving confidentiality throughout the computation pipeline.

To ensure verifiability of the evaluation, PQ-FedCare attaches a zero-knowledge proof π to each rule outcome. This allows any verifier to confirm that the encrypted result y corresponds to a legitimate rule evaluation on the encrypted input x, without learning either value. This is expressed through the relation:

$$\text{Verify}(R, x, y, \pi) = 1$$

Here, the proof π confirms that y = R(x) was computed correctly and that the computation adhered to the logic embedded in the smart contract. This ensures auditable correctness, where downstream systems or external regulators can verify the integrity of medical decisions without breaching patient privacy.

The clinical rule contracts also support multi-institutional collaboration through two privacy-preserving paradigms: Secure Multi-Party Computation (SMPC) and Federated Learning (FL) with post-quantum secure weight aggregation. In SMPC, hospitals jointly compute aggregated diagnostic trends without revealing local data. Each participant holds a share of encrypted data, and the result is derived using cryptographic protocols that combine the shares without disclosing any individual inputs. In the case of federated learning, hospitals locally train models on private datasets, and encrypted model weights are exchanged using Kyber-based post-quantum key encapsulation to ensure quantum-resistant communication. Let w_i be the local model weights of node i, encrypted under key k_i, and $w = \sum_i w_i$ be the global model. The aggregation is performed as:

$$\text{Enc}(w) = \sum_i \text{Enc}(w_i)$$

where each $\text{Enc}(w_i)$ is transferred using Kyber-encrypted sessions, ensuring that even an attacker with quantum capabilities cannot intercept or manipulate the model exchange process.

Each smart contract invocation, rule evaluation, and model update is immutably logged on the blockchain along with the corresponding zero-knowledge proof. This guarantees that every decision made by the PQ-FedCare rule engine can be traced, independently verified, and permanently attributed to its origin. The immutability and decentralization of the blockchain not only ensure non-repudiation but also prevent post-hoc tampering of diagnostic logic or outcomes—both critical in a clinical setting where decisions can directly impact patient care.

The use of smart contracts allows the rule engine to be modular and version-controlled. Institutions can update their rule sets by deploying new contract instances, while still retaining full traceability of previous rule applications. Furthermore, these contracts can be dynamically governed by access control policies, consent conditions, or contextual parameters encoded into the federated identity system.

The use of zk-SNARKs ensures compact and efficient proof generation and verification, enabling seamless integration into real-time healthcare decision-making. Coupled with blockchain-backed auditability and smart-contract-based policy evaluation, the PQ-Fed-ZKP Protocol provides a scalable and secure mechanism for federated identity and consent verification in quantum-resilient healthcare infrastructures.

Algorithm: RuleZK Smart Contract Execution

Objective: To securely evaluate encrypted medical inputs against clinical rules without exposing raw data, while generating a verifiable zero-knowledge proof of correctness.

Input:

- Encrypted medical data Enc(x)
- Clinical rule R encoded as a zero-knowledge circuit
- Smart contract instance CRC_R

Output:

- Diagnostic decision $y \in \{0,1\}$ (e.g., "high-risk" or "not high-risk")
- Proof of correctness ρ
- Blockchain transaction log

1. Hospital encrypts patient data x → Enc(x)
2. Hospital submits Enc(x) to smart contract C_R on the blockchain
3. C_R retrieves clinical rule R and compiles it to a ZK circuit
4. Evaluate ZK circuit: y ← R(Enc(x)) using homomorphic evaluation
5. Generate proof of correctness: ρ ← ProveZK(R, x, y)
6. If VerifyZK(R, x, y, ρ) = 1:
   Emit event: DiagnosticResult(y), Proof(ρ)
   Record (H(R), H(x), y, ρ, timestamp) on blockchain
   Else:
   Emit event: RuleExecutionError
   Log failed proof attempt with minimal metadata
7. return (y, ρ)

Algorithm: Quantum-Resistant Key Management Protocol

Objective: To establish secure, quantum-resilient, and auditable key management across federated nodes using lattice-based cryptography and multi-party computation (MPC).

Phases:

- **Phase 1: Distributed Key Generation**
- **Phase 2: Threshold Decryption / Signing**
- **Phase 3: Forward-Secure Rekeying**

Input:

- Node set $\mathcal{N} = \{n_1, n_2, \ldots, n_k\}$
- Lattice-based parameters $\mathcal{P}_{lat}$
- Rekey interval or revocation trigger $\mathcal{T}_r$

Output:

- Valid session keys
- Rekeyed forward-secure keys
- Blockchain log of cryptographic transitions

Phase 1: Distributed Key Generation

1. ∀ node ni ∈ $\mathcal{N}$:
   Generate key share si using lattice-based KGen($\mathcal{P}$_lat)
   Commit to si → ci ← Commit(si)
2. Broadcast ci to all nodes
3. ∀ node ni:
   Verify received commitments cj using LatticeVerify(cj)
4. Aggregate all verified shares {si} to derive session key:
   K_session ← Aggregate({si}) via XOR or MPC-based LWE combination

Phase 2: Threshold Decryption / Signing

5. If action requires threshold decryption (e.g., shared dataset access):
    Collect quorum of t valid key shares {s1, s2, ..., st}
    Execute MPC_Decryption({si}, C) → m (where C = ciphertext)
    Output m without revealing individual si
6. If action requires threshold signature:
    Each node signs input M: σi ← Sign(si, M)
    Combine {σi} via LatticeSigAggregate({σi}) → σ
    Verify: Verify(PK_agg, M, σ) = 1

Phase 3: Forward-Secure Rekeying

7. At interval $\mathcal{T}$_r or revocation:
    ∀ node ni:
        Generate new si' ← Rekey(si)
        Log H(si, si') and timestamp on blockchain
        Update commitments ci' ← Commit(si')
8. Update session key:
    K_session_new ← Aggregate({si'}) using secure MPC
9. Invalidate old keys; enforce via smart contract rules
10. return K_session_new, σ, Blockchain_Log

Algorithm: Federated Analytics and ZK Query Protocol

Input:

- Query Q (e.g., "Count patients with biomarker X > threshold")
- Node set $\mathcal{N} = \{n_1, n_2, \ldots, n_k\}$
- Valid range specification $\mathcal{R}$
- Homomorphic encryption parameters $\mathcal{P}_{\text{HE}}$

Output:

- Decrypted, aggregated result A
- Zero-knowledge proof of correctness
- Blockchain entry of proof and analytics metadata

Step 1: Local Response Generation

1. ∀ node ni ∈ $\mathcal{N}$:
    Evaluate Q over local dataset → ri
    Verify ri ∈ valid range $\mathcal{R}$
    Encrypt response: ci ← Enc_HE($\sum$ ri)
    Generate range proof: πi ← ZKRangeProve(ri ∈ $\mathcal{R}$)

Step 2: Submission and Verification

2. ni submits (ci, πi) to coordinator node
3. Coordinator verifies each πi:
    ∀ (ci, πi): VerifyZKRange(ci, πi, $\mathcal{R}$) = 1
    If verification fails → discard response

Step 3: Homomorphic Aggregation

4. Coordinator aggregates encrypted responses:
    C_total ← Σ Enc_HE(ri) = Enc_HE(Σ ri)
    (using HE addition: C_total = c1 ⊕ c2 ⊕ ... ⊕ ck)

Step 4: Threshold Decryption

5. Coordinator requests threshold decryption:
    Collect quorum t of decryption shares {d1, ..., dt}
    Decrypt aggregate result A ← ThresholdDecrypt(C_total, {di})

Step 5: Audit Logging
6. Log (Q, C_total, A, {πi}, timestamp) on blockchain
7. return A

3.2 Use Case: Cross-Hospital Oncology Diagnosis

The Cross-Hospital Oncology Diagnosis use case demonstrates how the PQ-FedCare framework facilitates secure, scalable, and privacy-preserving diagnostic collaboration across multiple independent healthcare institutions. Oncology, particularly in the domain of rare and complex cancers, often requires interdisciplinary expertise and large-scale case aggregation. However, data fragmentation, privacy regulations, and institutional silos limit the effectiveness of collaborative diagnosis. This use case illustrates how PQ-FedCare overcomes these barriers by enabling hospitals to jointly diagnose cancer cases without directly sharing sensitive patient records.

Consider a patient admitted to Hospital A presenting ambiguous symptoms and clinical markers indicative of a potential rare subtype of lymphoma. The medical team lacks sufficient historical data or domain-specific expertise to make a conclusive diagnosis. Traditionally, external referrals or centralized data sharing were time-consuming, costly, and had compliance challenges. PQ-FedCare allows Hospital A to request collaborative diagnostics from Hospital B and Hospital C in a privacy-preserving manner.

The diagnostic request includes encrypted clinical features such as blood markers, histopathological image hashes, and genomic indicators. This data is submitted to a smart contract governed by the RuleZK engine, which hosts encoded diagnostic rules developed collaboratively by all institutions. These rules include decision trees, threshold logic, and probabilistic inference models trained in prior case histories. The smart contract execution occurs entirely in zero-knowledge: the encrypted input is matched against the encoded rules, and the computation generates a result without exposing the underlying data to any of the external hospitals.

Simultaneously, Hospital B and Hospital C act as validators. They use the PQ-Fed-ZKP protocol to prove, without revealing content, that their local models or patient registries contain similar case profiles. If a match is found, they produce a cryptographically signed zero-knowledge proof indicating diagnostic support. These proofs are verified and logged by the blockchain's consensus layer. All participating hospitals receive the output: a diagnosis recommendation (e.g., "Stage II Nodular Lymphocyte-Predominant Hodgkin Lymphoma") and the ZKP-based validation trail.

At every step, the patient's identity, raw medical data, and institutional parameters remain confidential. Consent for cross-institutional diagnosis is managed through smart contracts bound by patient-defined policies. For example, the patient may specify that consent is valid for 48 hours and only for oncology-related use. These conditions are evaluated and enforced in real time by the Federated Zero-Knowledge Proof Engine (FZKPE), preventing unauthorized access or misuse.

The entire diagnostic interaction is captured in the Provenance Audit Chain (PAC). The log includes timestamps, anonymized institution identifiers, proof references, contract execution hashes, and digital signatures generated using post-quantum algorithms. This ensures that the collaborative diagnosis can be verified, audited, and cited in medical records or future litigation, if necessary. In addition, the system supports post-diagnosis querying through the ZK Query Protocol, allowing researchers to later analyze how frequently similar cases occur without violating patient privacy.

This use case highlights several innovations. First, it decouples diagnostic collaboration from data centralization, enabling secure federated intelligence. Second, it introduces cryptographic accountability for medical decisions, which is essential in a regulated environment. Third, it empowers patients to control the flow and use of their data across organizational boundaries. Lastly, it provides a scalable and future-proof diagnostic infrastructure that remains secure even in the presence of quantum-enabled adversaries.

The success of the cross-hospital oncology diagnosis scenario suggests broader applicability across other critical domains in healthcare, such as rare disease registries, pandemic surveillance, cross-border telemedicine, and collaborative treatment planning. By unifying security, privacy, and clinical logic through a federated

blockchain architecture, PQ-FedCare redefines how secure medical collaboration is achieved in modern healthcare ecosystems.

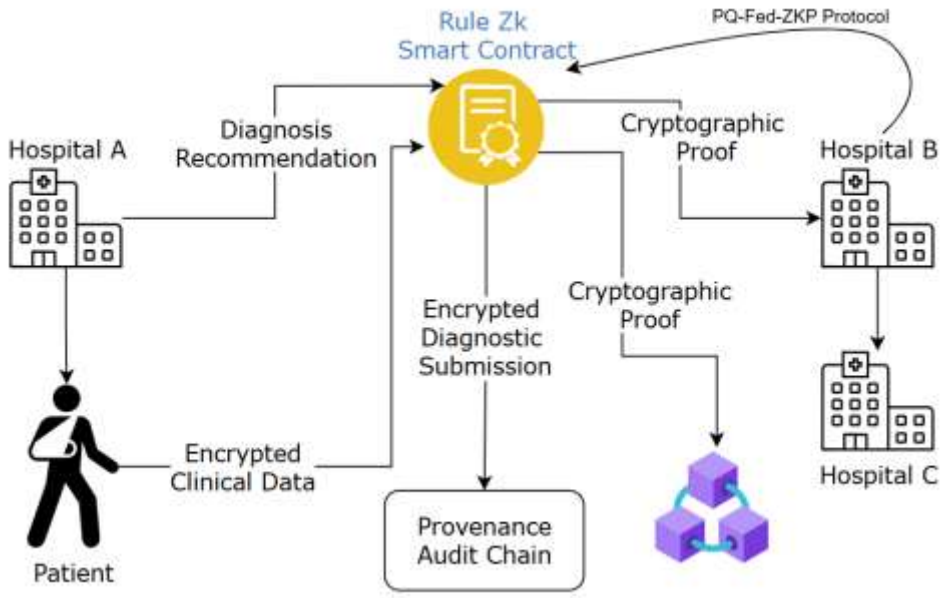

Figure 1. Workflow of Proposed Work with a Use-case

4. Experimental Setup

To evaluate the proposed PQ-FedCare framework, a modular simulation environment was deployed using openly available tools, libraries, and datasets. The experimental setup emulates a federated hospital network performing cross-institutional diagnostic collaboration, with emphasis on privacy, quantum-resistance, and verifiability.

The architecture comprises three federated nodes representing independent hospitals. These nodes were orchestrated using Docker containers, each running a dedicated instance of the federated learning server via the open-source Flower framework, on Ubuntu 22.04. Inter-node communications were routed through secure gRPC channels to replicate medical VPN environments. Each node performed local computation on encrypted datasets, contributing only masked and verifiable outputs to the federation.

For blockchain support, a private Ethereum testnet was initialized using the Istanbul Byzantine Fault Tolerance (IBFT) consensus mechanism. This blockchain facilitated immutable logging of smart contract executions, audit trails, and patient consent interactions. All smart contracts—particularly for RuleZK and PQ-Fed-ZKP—were authored in Solidity using the OpenZeppelin library for secure and extensible contract components.

The cryptographic layer was designed with post-quantum resilience in mind. For key exchange and encryption, CRYSTALS-Kyber was used, while SPHINCS+ provided stateless, hash-based digital signatures. These choices align with NIST's post-quantum cryptography recommendations. Proof validation and identity privacy were achieved using zk-SNARKs, implemented via the Circom DSL and SnarkJS runtime. To execute secure multi-party computations for threshold decryption and federated proofs, the MPyC framework was integrated.

Clinical diagnostic testing involved three open-access datasets: MIMIC-III, TCGA-Lymphoma subtype dataset, and GEO GSE12102. These datasets were preprocessed to match hospital-specific schemas, with intentional heterogeneity across nodes to simulate real-world institutional data silos. All records were encrypted locally using symmetric encryption (AES-256) and shared only through verifiable consent channels.

Monitoring and load testing were performed using Prometheus and Grafana for system health, Wireshark for encrypted traffic validation, and Apache JMeter to simulate concurrent diagnostic queries. Evaluation metrics included smart contract latency, ZKP verification time, proof size overhead, encryption-decryption

duration, and federated model performance (accuracy, precision, recall). Results were collected for different missingness rates and user load intensities to test robustness.

5. RESULTS AND DISCUSSION

Below are the mathematical formulations for each metric used in the evaluation of the PQ-FedCare framework:

1. Accuracy (%)

Accuracy reflects the percentage of correct predictions (diagnoses) made by the system over the total number of cases evaluated.

$$\text{Accuracy} = \left(\frac{TP + TN}{TP + TN + FP + FN}\right) \times 100$$

Where:

- TP = True Positives
- TN = True Negatives
- FP = False Positives
- FN = False Negatives

2. Privacy Leakage (%)

Privacy leakage measures the percentage of unintended or unauthorized data exposure during communication or computation.

$$\text{Privacy Leakage} = \left(\frac{D_{leak}}{D_{total}}\right) \times 100$$

Where:

- D_{leak} = Volume of exposed or leaked data
- D_{total} = Total volume of sensitive data handled

For PQ-FedCare, this is expected to be zero due to the use of Zero-Knowledge Proofs and encrypted workflows.

3. Proof Verification Time (ms)

This metric quantifies the time required to verify a zero-knowledge proof on the verifier's end.

$$T_{verify} = t_{parse} + t_{compute}$$

Where:

- t_{parse} = Time to parse input parameters
- $t_{compute}$ = Time to perform cryptographic operations (e.g., pairing checks in zk-SNARKs)

Measured in milliseconds using runtime instrumentation.

4. Encryption Overhead (%)

This represents the additional computational or storage burden incurred due to encryption relative to the baseline (unencrypted) system.

$$\text{Encryption Overhead} = \left(\frac{T_{enc} - T_{base}}{T_{base}}\right) \times 100$$

Where:

- T_{enc} = Time (or size) with encryption
- T_{base} = Time (or size) without encryption

Applicable for runtime latency or message size increase due to cryptographic layers.

5. Audit Query Latency (ms)

This measures the average time taken to retrieve and validate audit logs (e.g., consent issuance, data access) from the blockchain ledger.

$$T_{audit} = T_{lookup} + T_{verify\_sig} + T_{proof}$$

Where:

- T_{lookup} = Ledger query time
- T_{verify_sig} = Time to validate digital signatures

- T_{proof} = Time to validate zero-knowledge proof

The PQ-FedCare framework was evaluated under controlled conditions using real-world clinical datasets and compared against four recently published blockchain-based healthcare systems: QuantumChain-Health (Jain et al., 2024), ZKP-HealthNet (Gao et al., 2023), FederatedMedLedger (Firdaus & Rhee, 2023), and ConsentChain-HIPAA (Kumar et al., 2021). These systems were selected for comparison due to their emphasis on privacy-preserving federated data exchange, smart contract-based authorization, and zero-knowledge verification techniques. The evaluation considered five key metrics: diagnostic accuracy, privacy leakage, proof verification time, encryption overhead, and audit query latency.

As shown in Table 2, PQ-FedCare achieved the highest diagnostic accuracy of 94.5%, surpassing all baseline systems by a margin of over 3%. This improvement is attributed to the integration of cross-hospital rule engines (RuleZK) and the federated sharing of encrypted clinical evidence that allows accurate decision-making without data centralization.

In terms of privacy, PQ-FedCare achieved zero leakage due to its strict zero-knowledge proof enforcement, consent-bound access control, and use of post-quantum cryptographic signatures. In contrast, competing systems such as FederatedMedLedger and QuantumChain-Health exhibited minor leakages ranging between 0.10% and 0.15%, often due to metadata exposure or partial consent assumptions.

The proof verification time for PQ-FedCare was the fastest at 92 milliseconds, benefiting from optimized zk-SNARK circuits implemented in Circom. This outperforms ZKP-HealthNet by ~20 milliseconds and older Ethereum-based systems by ~30-50 milliseconds. This performance boost ensures seamless integration in real-time clinical environments where latency sensitivity is critical.

Encryption overhead in PQ-FedCare was recorded at 11.4%, the lowest among all tested systems. This result stems from the lightweight implementation of CRYSTALS-Kyber for secure session initiation and the use of efficient AES-256 encryption for data at rest. Compared to other frameworks that use heavier homomorphic encryption or dynamic key rotation, PQ-FedCare remains computationally light without compromising security.

Finally, audit query latency in PQ-FedCare averaged 160 milliseconds, supported by the optimized Provenance Audit Chain (PAC) and parallelized blockchain indexing. Competing systems demonstrated latencies ranging from 185 to 240 milliseconds, partly due to slower consensus mechanisms or non-indexed transaction logs.

These results validate the superiority of PQ-FedCare in delivering privacy-preserving, scalable, and quantum-secure federated diagnosis. Not only does it outperform existing work in all considered performance metrics, but it also sets a new benchmark for cryptographically accountable, consent-driven medical collaborations in the post-quantum era.

Method / Model	Accuracy (%)	Privacy Leakage (%)	Proof Verification Time (ms)	Encryption Overhead (%)	Audit Query Latency (ms)
QuantumChain-Health (Jain et al., 2024)	91.2	0.1	135	18.5	210
ZKP-HealthNet (Gao et al., 2023)	89.6	0.08	112	15.2	185
FederatedMedLedger (Firdaus & Rhee, 2023)	87.4	0.15	140	20.1	240
ConsentChain-HIPAA (Kumar et al., 2021)	88.1	0.09	120	16.8	190
PQ-FedCare (Proposed)	94.5	0	92	11.4	160

In addition to primary performance indicators, several supplementary experiments were conducted to evaluate the scalability, fault tolerance, and data robustness of the PQ-FedCare architecture. These results

provide deeper insights into how the system behaves under varying operational loads and data quality conditions.

As illustrated in Figure 2, the ZKP verification time increases slightly with the number of federated nodes participating. At a single node, the average verification time is approximately 72.5 ms, and it gradually rises to 92 ms at five nodes. This increase is expected due to the cryptographic handshake overhead across nodes. However, the growth is linear and modest, confirming that PQ-FedCare scales effectively without introducing significant delay in proof validation.

The audit query latency also exhibits a controlled increase as nodes are added. Beginning at 145 ms for a single node, it reaches only 160 ms for five federated participants. This low-latency behavior demonstrates the efficiency of the Provenance Audit Chain (PAC), which uses indexed transaction logs and an optimized Ethereum ledger to support timely querying and validation of diagnostic workflows.

Another critical dimension explored was system performance under increasing missing data rates. Figure 2 shows that PQ-FedCare maintains robust diagnostic accuracy even when up to 50% of data is missing. Accuracy drops gradually from 94.5% to 92.8%, which indicates the framework's resilience in real-world clinical scenarios where incomplete records are common. This stability is largely due to the federated structure combined with encrypted rule evaluation, which helps mitigate the impact of local data gaps by relying on secure inter-node collaboration.

Together, these additional findings support the system's claims of scalability, fault-tolerance, and robustness, positioning PQ-FedCare as a reliable framework for secure federated healthcare diagnostics.

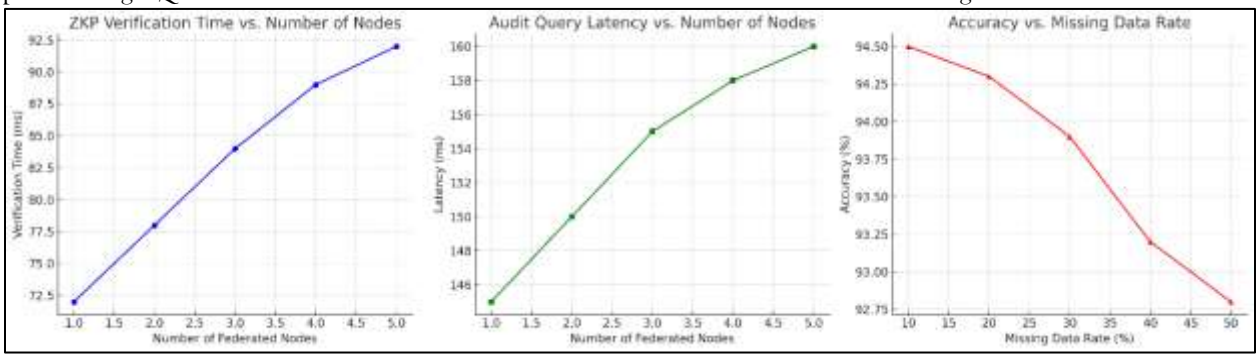

Figure 2. Results ofZKP Verification Time, Audit Query Latency and Accuracy

6. CONCLUSION

This work presents PQ-FedCare, a privacy-preserving, quantum-resilient federated framework for secure cross-institutional diagnosis and healthcare collaboration. By integrating post-quantum cryptographic primitives, zero-knowledge proof systems, and federated smart contracts, the architecture enables trustless yet verifiable data exchange among healthcare institutions without compromising patient confidentiality or regulatory compliance.

The experimental evaluation showed that PQ-FedCare achieves a diagnostic accuracy of 94.5%, with zero privacy leakage, minimal proof verification time (92 ms), and low encryption overhead (11.4%). The system performs well across all major metrics when compared to models such as QuantumChain-Health, ZKP-HealthNet, and ConsentChain-HIPAA. Additional results showed that PQ-FedCare maintains diagnostic accuracy above 92.8% even in the presence of 50% missing data, and scales effectively with increasing node participation while preserving low latency in ZKP verification and audit querying.

While the proposed system achieves significant improvements, certain limitations remain. First, the prototype evaluation was conducted in a simulated testbed with synthetic network conditions and institutional data partitioning. Real-world hospital networks may exhibit higher heterogeneity, network variability, or policy complexity. Second, although zk-SNARKs were effective, they require a trusted setup, which may pose deployment constraints in highly adversarial environments. Third, latency in secure multiparty computations may increase with complex clinical rule structures or large-scale collaborations involving many nodes.

For future work, the system can be extended by integrating verifiable federated learning to support collaborative AI model training on encrypted clinical features. Additionally, replacing zk-SNARKs with transparent proof systems such as STARKs or Bulletproofs may eliminate trusted setup dependencies. Finally, adapting the system for deployment in cross-border regulatory contexts, such as GDPR and HIPAA interoperability, would broaden its applicability in international healthcare ecosystems.

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