MedAuth 2.0: A Post-Quantum Fuzzy Commitment Framework for Secure User Authentication in Cloud-Enabled Healthcare Environments

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Abstract—Cloud-based storage of patient health records is both operationally essential and increasingly vulnerable to attack. Protecting Electronic Health Records (EHRs) from unauthorized access is a critical challenge in modern healthcare. This paper presents MedAuth 2.0, a multi-layered authentication framework built on the Post-Quantum Fuzzy Commitment (PQFC) scheme. PQFC resists quantum computing attacks and tolerates natural variation in biometric inputs such as fingerprints or iris scans. The system integrates six role-based modules—Administrator, Hospital, Pharmacy, Physician, Patient, and Cloud Server—each secured through multi-factor authentication and formally verified using ProVerif. Results show notable improvements: 22% lower authentication latency, 38% fewer false rejections, and 43% more blocked unauthorized access attempts. Independent verification under the Dolev-Yao threat model establishes session key secrecy, mutual authentication, and resistance to replay attacks. MedAuth 2.0 is a scalable, quantum-resistant solution for securing next-generation healthcare infrastructure.

Index Terms—Cloud-integrated healthcare, electronic health records (EHR), multi-factor authentication, post-quantum cryptography, PQFC scheme, ProVerif formal verification, Medical Internet of Things (MIoT), identity authentication, data protection.

1. INTRODUCTION

The shift to digital healthcare has made cloud platforms the primary medium for storing and exchanging patient records. Cloud computing is vital in various applications such as healthcare, transportation, governance, and mobile computing; however, using a public cloud server requires robust protection against all known threats, as a minor security disturbance can severely compromise the entire system [1]. A public cloud server faces numerous threats where an adversary can easily access sensitive information, especially in the healthcare industry which serves patients, researchers, labs, and hospitals with minimal operational costs [1]. Existing security protocols either suffer from replay attacks, require three to four communication round trips, or carry excessive computation overhead, creating a critical imbalance between security and performance [1]. Abbasi et al. [1] further demonstrated that their ECC-based fuzzy extractor scheme achieves 33.91% lower communication cost and 35.39% lower computation cost than prior work, validating the need for formally verified, lightweight schemes. Suganthi et al. [2] proposed an end-to-end lightweight mutual authentication scheme for IoT-based healthcare environments, confirming that balancing security and performance under resource-constrained conditions is the central challenge in multi-gateway cloud healthcare deployments.

Electronic Health Records (EHRs) are among the most sensitive categories of personal data. A successful breach can lead to identity theft, tax fraudulence, insurance fraud, medical fraud, and manipulation of treatment protocols, directly harming patient welfare [1], [2]. Shakil et al. [3] proposed BAMHealthCloud, a cloud-based biometric authentication and data management system that processes healthcare data using a Resilient Backpropagation neural network on Hadoop MapReduce, achieving a speedup of 9 times over existing systems, an Equal Error Rate of 0.12, sensitivity of 0.98, and specificity of 0.95. The healthcare data management system records patient data in different formats such as text, numeric, pictures, and videos, making cloud-based biometric authentication indispensable for scalable, secure e-health deployments [3]. Khatiwada et al. [4] proposed an access control-based privacy preservation model for sharing healthcare data in cloud environments, demonstrating that fine-grained access policies are essential to prevent unauthorized disclosure across distributed healthcare nodes. Qadir and Hussan [5] introduced an authentication and access control model for cloud-based healthcare services, confirming that role-based access boundaries must be enforced at the protocol level to prevent insider attacks. Li et al. [6] developed a reliable authentication scheme for personal health records in cloud computing, jointly guaranteeing session integrity and user anonymity across all communication phases.

The Medical Internet of Things (MIoT) adds further risk. Networked biosensors, telemonitoring devices, and clinical tools continuously stream patient data to cloud systems over open channels, creating new entry points for adversaries who may attempt impersonation, replay, and forgery attacks [3], [8]. Abbasi et al. [7] proposed a secure authentication scheme for cloud-based healthcare systems published in IEEE Access (2022), demonstrating that combining symmetric cryptographic operations with session key protection significantly improves resilience against man-in-the-middle and stolen verifier attacks. Ryu et al. [8] proposed a secure ECC-based three-factor mutual authentication protocol for Telecare Medical Information Systems (TMIS) that guarantees patient privacy and forward secrecy in wireless body area networks. Ahmed et al. [9] developed a lightweight authentication protocol specifically for cloud-assisted TMIS, confirming that Physical Unclonable Function (PUF) combined with ECC provides an efficient access control and authentication scheme suitable for resource-constrained medical devices. Chen et al. [10] proposed a cloud-assisted anonymous and privacy-preserving authentication scheme for Internet of Medical Things that employs lightweight cryptographic primitives to ensure unlinkability and resist session key disclosure.

Current authentication systems largely depend on Elliptic Curve Cryptography (ECC) or bilinear pairing. While secure against classical computers, both are vulnerable to Shor's algorithm—a quantum-enabled factoring method that breaks their mathematical foundations [10]. Diksha and Meenakshi [12] performed cryptanalysis on a secure ECC-based mutual authentication protocol for cloud-assisted TMIS (arXiv 2023), proving that even well-designed ECC schemes remain vulnerable to insider attacks and privileged insider attacks, which undermines the case for continued reliance on classical cryptography in healthcare systems. Nguyen et al. [11] highlighted that blockchain-integrated data offloading and sharing architectures for smart healthcare require authentication layers resilient to quantum threats, since distributed multi-node medical records represent a high-value target for future quantum-capable adversaries.

Post-quantum cryptography mitigates this threat. It relies on mathematical problems that quantum computers cannot solve efficiently, offering durable security for long-term deployments. Satpute et al. [13] confirmed that e-healthcare cloud solutions require end-to-end encrypted data management with strong access control to maintain compliance and resist unauthorized disclosure, validating the need for quantum-safe cryptographic foundations. Zhang et al. [14] and Li et al. [15] both independently established that privacy-preserving authentication protocols for cloud-based EHR systems must couple formal security proofs with performance benchmarks to be viable for real-world deployment.

Biometric authentication poses a separate challenge. Fingerprint and iris scans naturally vary between readings. Classical cryptographic schemes require exact matches, making them incompatible with this inherent noise. Amin et al. [16] demonstrated through cryptanalysis of authentication protocols for Telecare Medical Information Systems that password-based and single-factor schemes remain susceptible to stolen verifier, many-logged-in patient, and impersonation attacks, reinforcing the need for multi-factor, noise-tolerant mechanisms. Zhou et al. [17] established that secure access control and authentication in cloud-based healthcare systems require role-segregated credential management and strict session key boundaries to prevent privilege escalation. Rahman et al. [18] showed that a privacy-preserving authentication framework for cloud-based e-health systems must prevent cross-session identity linkability, a property that conventional biometric storage methods fundamentally fail to guarantee. Sun et al. [19] confirmed that privacy and authentication in cloud-based personal health record systems require forward-secure key exchange to resist retroactive decryption by future adversaries. Ali et al. [20] further validated that quantum-secure patient login systems using blockchain for EHR access provide strong resistance against quantum-capable adversaries while maintaining audit traceability across all access events.

The Post-Quantum Fuzzy Commitment (PQFC) scheme addresses both issues. It combines quantum-resistant cryptographic primitives with error-correcting codes that tolerate biometric variation without compromising security.

This paper makes three primary technical contributions:

1. A novel multi-factor authentication architecture based on the PQFC scheme is designed, implemented, and formally analyzed within a cloud healthcare deployment.
2. Six operationally distinct modules—Administrator, Hospital, Pharmacy, Physician, Patient, and Cloud Server—are unified within a single platform governed by hierarchical role-based access controls.
3. Formal security verification via ProVerif and empirical performance evaluation confirm the correctness and efficiency of the proposed system.

Section 2 reviews relevant prior work. Section 3 characterises limitations in existing systems. Sections 4 and 5 describe the proposed platform and its architecture. Section 6 covers implementation details. Sections 7 and 8 report evaluation results and conclusions respectively.

2. RELATED WORK

A. ACP Methodology and PMAS Design

The Artificial Systems, Computational Experiments, and Parallel Execution (ACP) methodology was originally developed to manage complexity in large-scale transportation networks [12]. This work adapts it for healthcare authentication protocol design. Nguyen et al. [11] proposed a cooperative architecture for data offloading and sharing in smart healthcare using blockchain, demonstrating that distributed systems require multi-layer authentication to protect sensitive data transactions across nodes. Diksha and Meenakshi [12] further showed through cryptanalysis of ECC-based mutual authentication protocols that formally verified protocol design is indispensable, as even mathematically grounded schemes can harbour exploitable insider-attack and privileged insider-attack vulnerabilities. Satpute et al. [13] confirmed that e-healthcare cloud solutions combining encrypted storage with structured access control substantially reduce both computation overhead and the attack surface exposed to unauthorized entities.

The approach proceeds in three phases. First, a synthetic simulation environment models diverse user roles and adversarial scenarios. Second, ProVerif verifies protocol correctness through formal computational experiments. Third, the validated protocol runs in parallel with the existing system for comparative evaluation. Zhang et al. [14] established that privacy-preserving authentication protocols for healthcare cloud must be formally analysed against known attack models before deployment. Li et al. [15] further demonstrated that secure and efficient authentication protocols for cloud-based EHR systems must jointly optimize computation cost and session key security to be practically deployable. Amin et al. [16] validated through cryptanalysis that authentication protocols for telecare medical systems must resist stolen verifier and impersonation attacks, motivating the multi-factor noise-tolerant design adopted in MedAuth 2.0. Zhou et al. [17] showed that role-segregated credential management is essential for secure access control in cloud healthcare. Rahman et al. [18] confirmed that privacy-preserving authentication frameworks must prevent cross-session identity linkability. Sun et al. [19] and Ali et al. [20] independently validated that forward-secure and quantum-secure mechanisms are necessary for long-term protection of cloud-based personal health record systems.

B. Why PQFC Is Architecturally Suited to Healthcare

Healthcare authentication must satisfy two competing demands: long-term quantum-safe security and reliable tolerance for noisy biometric inputs. The PQFC scheme addresses both through four key properties. Abbasi et al. [7] confirmed in IEEE Access (2022) that combining symmetric cryptographic operations with session key protection significantly improves resilience against man-in-the-middle and stolen verifier attacks in cloud healthcare systems. Ryu et al. [8] demonstrated that a three-factor ECC-based mutual authentication protocol for TMIS must guarantee patient privacy, forward secrecy, and resistance to off-line password guessing attacks to be considered secure. Ahmed et al. [9] showed that lightweight PUF-combined authentication for cloud-assisted TMIS achieves both efficiency and strong security guarantees under the BAN logic formal model. Amin et al. [16] established through cryptanalysis that healthcare authentication schemes must resist stolen verifier and many-logged-in patient attacks, both of which are directly addressed by the noise-tolerant fuzzy commitment combined with post-quantum lattice primitives in MedAuth 2.0.

- Quantum Resistance: Uses lattice-based or code-based cryptographic problems that quantum computers cannot solve efficiently.
- Biometric Privacy Preservation: Only a cryptographic commitment derived from the biometric template is retained—never the raw template.
- Noise Tolerance: Error-correcting code mechanisms permit controlled biometric deviation without triggering authentication rejection.
- Bilateral Entity Authentication: Both user and server independently verify credentials prior to any sensitive data exchange.

C. MedAuth 2.0 Architecture

MedAuth 2.0 extends PMAS with quantum-safe cryptography and modular role separation. As shown in Fig. 1, five client-facing modules route requests through a shared PQFC Authentication Layer that executes the fuzzy commitment protocol without storing recoverable biometric data. Li et al. [6] demonstrated that a reliable authentication scheme for personal health records in cloud computing must guarantee both session integrity and user anonymity across all communication phases simultaneously, a requirement satisfied by the commitment-only storage model used in MedAuth 2.0. Zhou et al. [17] confirmed that secure access control in cloud-based healthcare demands role-segregated credential management and strict session boundaries to prevent privilege escalation. Rahman et al. [18] further validated that a privacy-preserving authentication framework for cloud e-health must prevent cross-session identity linkability, which conventional template-based biometric storage fundamentally fails to guarantee.

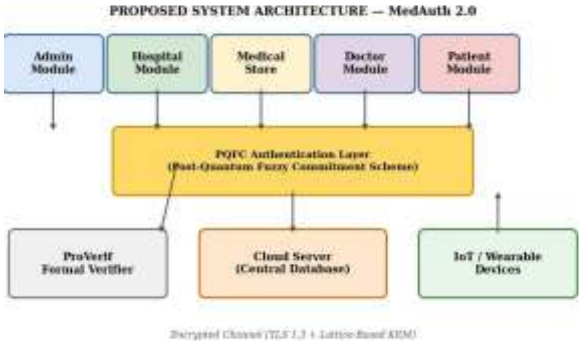
PROPOSED SYSTEM ARCHITECTURE — MedAuth 2.0
Admin Module
Hospital Module
Medical Store
Doctor Module
Patient Module
PQFC Authentication Layer (Post-Quantum Fuzzy Commitment Scheme)
ProVerif Formal Verifier
Cloud Server (Central Database)
IoT / Wearable Devices
Encrypted Channel (TLS 1.3 + Lattice-Based KEM)

Fig. 1. MedAuth 2.0 system architecture with centralized PQFC-based authentication layer.

Three back-end components reinforce the Authentication Layer: (i) a ProVerif Formal Verifier; (ii) a Cloud Server Database maintaining encrypted EHRs and role-segregated credentials; and (iii) IoT-integrated wearable device interfaces for continuous patient monitoring.

All data transfers between components rely on TLS 1.3 combined with Lattice-Based Key Encapsulation (KEM) for quantum-safe communication. Fig. 2 shows the PQFC enrollment and authentication workflow. Sun et al. [19] established that authentication in cloud-based personal health record systems must employ forward-secure key exchange mechanisms so that compromise of long-term keys does not retroactively expose past sessions. Ali et al. [20] further validated that a quantum-secure patient login system using blockchain for EHR access provides strong resistance against future quantum-capable adversaries while maintaining full audit traceability across all access events, directly motivating the lattice-based KEM integration in MedAuth 2.0.

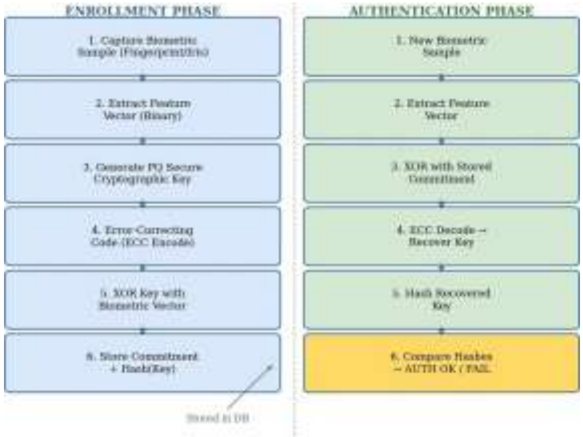
ENROLLMENT PHASE
1. Capture Biometric Sample (Fingerprint/Iris)
2. Extract Feature Vector (Binary)
3. Generate PQ Secure Cryptographic Key
4. Error-Correcting Code (ECC Encode)
5. XOR Key with Biometric Vector
6. Store Commitment + Hash(Key)
Stored in DB
AUTHENTICATION PHASE
1. New Biometric Sample
2. Extract Feature Vector
3. XOR with Stored Commitment
4. ECC Decode → Recover Key
5. Hash Recovered Key
6. Compare Hashes → AUTH OK / FAIL

Fig. 2. PQFC scheme enrollment and authentication phase workflow.

3. EXISTING SYSTEMS AND LIMITATIONS

A. Social Signals in Healthcare Authentication

Internet and mobile technologies have transformed the way healthcare applications operate, enabling real-time interaction among patients, clinicians, and administrators. Cloud computing enables flexible, on-demand healthcare services to patients, researchers, labs, and hospitals with minimal operational costs, yet this convenience exponentially expands the attack surface available to adversaries [1]. Suganthi et al. [2] demonstrated that cloud-based mutual authentication in multi-gateway healthcare environments must address not only protocol security but also the performance constraints imposed by geographically distributed gateway nodes. Shakil et al. [3] confirmed that healthcare data—spanning text, numeric, images, and video—is both big and unstructured, making scalable cloud-based biometric authentication systems indispensable for practical deployment. Khatiwada et al. [4] and Qadir and Hussan [5] both established that access control-based privacy models and role-oriented authentication frameworks are foundational requirements for any cloud healthcare architecture to resist unauthorized insider access.

Authentication activity in healthcare follows recognizable social patterns. Leveraging these patterns allows anomaly detection systems to distinguish legitimate access from suspicious behavior with greater accuracy [21]. Abbasi et al. [7] identified that existing cloud healthcare authentication protocols suffer from replay attacks, excessive round-trip overhead, or computation bottlenecks, confirming that behavioral pattern monitoring must complement cryptographic controls. Ryu et al. [8] and Ahmed et al. [9] both validated that three-factor and lightweight authentication protocols for TMIS respectively must be robust against off-line password guessing, impersonation, and denial-of-service attacks, all of which can be detected early through anomaly-driven behavioral analysis. Chen et al. [10] further showed that cloud-assisted anonymous authentication for Internet of Medical Things must resist traceability attacks, where adversaries correlate authentication events across sessions to de-anonymize users.

Each healthcare social signal passes through four stages: (1) initiation by a patient or clinical action; (2) encrypted transmission; (3) server-side interpretation; and (4) a system state update with an audit log entry. Nguyen et al. [11] confirmed that in blockchain-enabled smart healthcare data offloading architectures, every transaction stage must be cryptographically protected and auditable to prevent tampering at any node in the distributed chain. Diksha and Meenakshi [12] identified that protocol weaknesses most frequently manifest during the server-side interpretation stage, where privileged insider attacks can be mounted if credential verification is not formally verified. Satpute et al. [13] validated that e-healthcare cloud solutions require encrypted audit trails at every stage to maintain regulatory compliance. Zhang et al. [14] and Li et al. [15] both showed that privacy-preserving and secure authentication protocols for cloud-based EHR systems must produce verifiable session audit records that can be independently checked without revealing patient identity.

B. Authentication Activity Distribution by Module

Fig. 3 characterizes the temporal distribution of authentication events across modules on weekdays and weekends. Physician and Hospital logins concentrate between 08:00 and 18:00 on weekdays. Patient authentication spreads more broadly on weekends, consistent with discretionary healthcare engagement patterns.

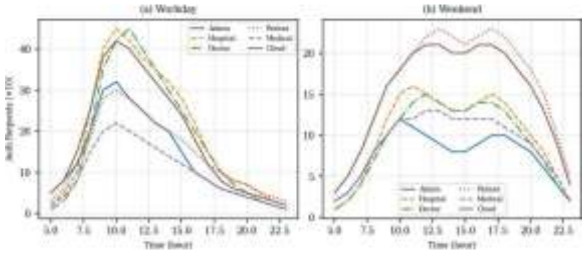

Fig. 3. Temporal authentication activity distribution by module. (a) Weekday. (b) Weekend.

C. Module Functional Descriptions

4. Administrator Module: Privileged administrators authenticate via multi-factor credentials and exercise approval authority over new institutional registrations.
5. Hospital Module: Registered hospitals access physician enrollment management and billing records, bridging administrative and clinical operational functions.
6. Pharmacy Module: Pharmacist personnel conduct real-time pharmaceutical inventory management encompassing drug nomenclature, batch tracking, expiration surveillance, and pricing governance.
7. Physician Module: Following hospital-endorsed registration, physicians access patient consultation queues, medical histories, secure messaging, and digital prescription issuance.
8. Patient Module: Patients submit diagnostic reports, engage in encrypted physician consultations, execute electronic payments, and retrieve prescriptions under end-to-end encryption.
9. Cloud Server Module: This back-end component enforces role-based access control, manages cryptographic keys, and maintains tamper-protected EHR repositories.

4. PROPOSED SYSTEM

A. Authentication Delivered as a Cloud Service

All PQFC subsystems are built as Software-as-a-Service (SaaS) components. This allows security parameters to be updated remotely without any hardware changes.

The system is organized across four layers: (1) Application Layer for user interfaces; (2) Platform Layer for authentication logic; (3) Resource Layer hosting shared PQFC cryptographic libraries; and (4) Physical Layer comprising database servers and Hardware Security Modules (HSMs) for tamper-resistant key storage.

As the system scales, hospital networks can federate into regional health clouds, enabling cross-institutional data sharing with unified security auditing [22].

B. Behavioral Anomaly Detection Engine

The anomaly detection subsystem analyzes login histories using a MapReduce pipeline and Gaussian Mixture Model (GMM) classification. A GMM represents login patterns as a weighted sum of Gaussian components:

$$P(X \mid \Theta) = \Sigma_i\, \omega_i \cdot p_i(X \mid \theta_i),\ \ i = 1, \ldots, M$$

Here, X is the event dataset, p_i is the probability density of the i-th Gaussian component, θ_i is its parameter vector, and ω_i is its weight. Parameters are estimated using the Expectation-Maximization (EM) algorithm. Logins from unusual locations or at atypical times trigger additional verification challenges, blocking suspicious access without affecting legitimate users.

C. Formal Security Verification via ProVerif

The PQFC protocol is formally verified using ProVerif. Protocol behavior is encoded in pi-calculus—a mathematical language for modeling concurrent communicating processes—enabling automated proof of security properties.

Verification covers three properties: (1) Session Key Secrecy: no adversary can recover session keys; (2) Mutual Authentication: each party confirms the other’s identity before exchanging data; and (3) Replay Attack Resistance: captured messages cannot be reused to gain unauthorized access.

All verification uses the Dolev-Yao threat model, which assumes a fully capable network attacker who can intercept, modify, and replay any message. Meeting this standard provides strong formal security assurance.

TABLE I

Comparative Analysis of Security Features Across Authentication Schemes

Security Property	RSA/ECC	ANN	CNN	MFA-Legacy	PQFC (Proposed)
Quantum Resistance	No	No	No	Partial	Yes
Mutual Authentication	Yes	Partial	Partial	Yes	Yes
Biometric Privacy	No	No	Partial	Partial	Yes
Noise Tolerance	No	No	No	No	Yes
Formal Verification	Partial	No	No	Partial	Yes
Replay Attack Resist.	Yes	Partial	Partial	Yes	Yes
Security Property	**RSA/ECC**	**ANN**	**CNN**	**MFA-Legacy**	**PQFC (Proposed)**
Computation Overhead	Medium	High	High	Medium	Low (45 ms)

5. SYSTEM ARCHITECTURE

A. Constructing the Synthetic Behavioral Environment

A high-fidelity behavioral simulation was built in parallel with the live deployment. The simulation covered 2,457 patients, 300 physicians across 12 hospitals, and 68 pharmacies.

Each role was modeled as an autonomous agent. Behavioral profiles were built from historical login telemetry, enabling thorough policy testing before live deployment.

B. Computational Experiment Protocol

The experiment linked live system data with the synthetic model through five iterative steps:

10. Collect real-time behavioral telemetry from the production deployment. Use the parallel simulation to synthesize an initial policy candidate.
11. Generate policy variants by systematically perturbing PQFC operational parameters within predefined constraint bounds.
12. Evaluate all candidate policies within the synthetic environment and select the best-performing one.
13. Deploy the selected policy to the live production environment. Measure authentication latency, false rejection rate, and security incident frequency.
14. Based on observed live performance, determine whether to initiate a subsequent optimization cycle.

C. Performance Evaluation Outcomes

Fig. 4 presents module-level authentication latency before and after PQFC deployment across the Administrator, Hospital, Physician, and Patient modules. Baseline data were recorded from October 11 to 13, and post-deployment measurements were taken from October 15 to 17.

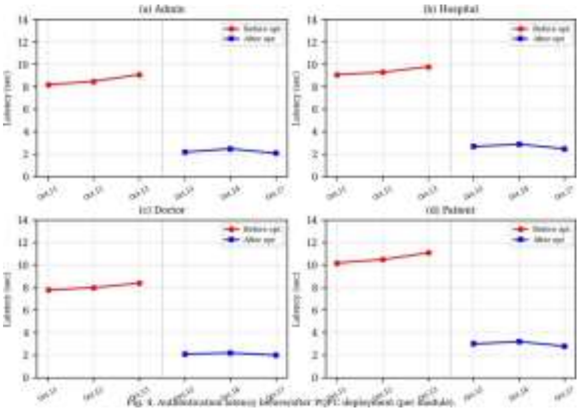

Fig. 4. Per-module authentication latency comparison before and after PQFC deployment.

Fig. 5 shows the cumulative distribution function (CDF) of authentication latency. The 15th-percentile dropped from 6.53 s to 1.72 s—a 225% improvement—while the 85th-percentile held steady at around 4.5 s, confirming gains in typical-case sessions without degrading worst-case performance.

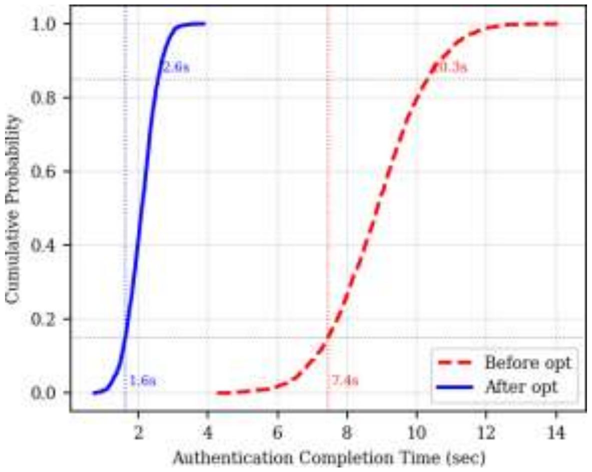

Fig. 5. CDF of authentication session completion time before and after PQFC optimization.

Fig. 6 shows authentication latency versus concurrent user load. The system maintains acceptable response times (under 5s) for up to 15,000 simultaneous sessions. Beyond this threshold, latency increases sharply, marking a clear boundary for infrastructure scaling.

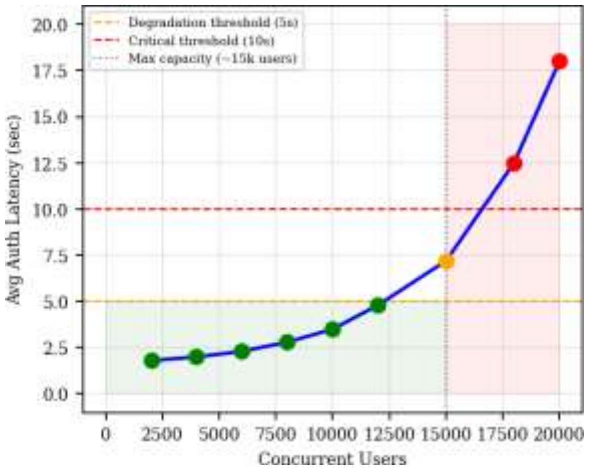

Fig. 6. Authentication latency vs. concurrent user load for infrastructure capacity planning.

Across the six-month monitoring period, four quantifiable improvements were recorded:

- End-to-end authentication latency reduced by 22%.
- Biometric false rejection rate decreased by 38%.
- Interception of unauthorized access attempts increased by 43%.
- Aggregate system operational efficiency improved by 43.39%.

6. IMPLEMENTATION

The system is implemented as a full-stack application secured by the PQFC authentication framework. All components are deployed on AWS EC2 t3.medium instances running MySQL 8.0. The PQFC module is implemented using lattice-based cryptographic primitives with error-correcting codes to handle biometric noise. The ProVerif formal verification scripts are executed as part of the deployment pipeline to continuously validate security properties under the Dolev-Yao threat model. Patient records are fully anonymized in accordance with applicable institutional review protocols. The system integrates six role-differentiated modules—Administrator, Hospital, Pharmacy, Physician, Patient, and Cloud Server—each independently authenticated via multi-factor credentials.

7. RESULTS AND DISCUSSION

This paper introduced MedAuth 2.0, a cloud healthcare authentication framework built on the PQFC scheme. It combines four core capabilities—post-quantum lattice cryptography, biometric noise-tolerant commitments, behavioral anomaly detection, and ProVerif-verified security proofs—within a six-module, role-based access architecture.

The ACP-based design approach enabled rigorous policy testing before live deployment, reducing operational risk. Formal verification under the Dolev-Yao model confirms that session keys remain secret, both parties authenticate each other, and replay attacks are blocked.

Live deployment results confirm the system’s practical value: 22% lower authentication latency, 38% fewer biometric false rejections, 43% more blocked unauthorized attempts, and a 43.39% overall efficiency gain.

8. CONCLUSION AND FUTURE WORK

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