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Zero-Trust Security Framework for AI Enabled Medical IoT Networks in Dental Implantology

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ABSTRACT

The integration of artificial intelligence (AI) with Internet of Medical Things (IoMT) devices in dental implantology has created unprecedented opportunities for real time monitoring, predictive analytics, and personalized treatment. However, this convergence also expands the attack surface across device communication, clinical infrastructure, and decision support pipelines. Traditional perimeter based security models are inadequate for the distributed, dynamic, and latency sensitive nature of modern dental implant networks. This paper presents a zero trust security framework specifically designed for AI enabled IoMT networks in dental implantology. The framework integrates three core innovations: (1) a hierarchical zero trust architecture with self sovereign identity based device admission and continuous verification, (2) a federated learning based intrusion detection system that preserves patient privacy while enabling collaborative threat intelligence across institutions, and (3) a publicly auditable evidence chain using post quantum cryptography and blockchain anchoring for tamper evident accountability. We validate the framework using a simulated dental implant monitoring network with 50 edge nodes, 200 IoMT devices, and three threat scenarios. Results demonstrate intrusion detection F1 score of 0.978, zero trust access control with sub 100ms latency, and complete audit trail verifiability. This work establishes that zero trust principles can be effectively applied to secure AI driven dental implant networks while maintaining clinical performance requirements.

Keywords

Zero-trust security, Dental implantology, Internet of Medical Things, Federated learning, Intrusion detection, Post-quantum cryptography.

Introduction

The digitization of dental implantology has accelerated dramatically over the past decade. Modern implant workflows now integrate cone-beam computed tomography (CBCT) imaging, AI-based treatment planning, robotic surgical navigation, and smart implant systems with embedded sensors for real-time stability monitoring. These interconnected systems collectively forming an Internet of Medical Things (IoMT) ecosystem enable data-driven, personalized implant care with unprecedented precision.

However, this connectivity introduces significant cybersecurity vulnerabilities. Dental implant networks connect clinical sensors, hospital systems, edge gateways, cloud services, and potentially patient-worn monitoring devices. Each connection point represents a potential entry vector for adversaries. Security failures in this context extend beyond data breach they can directly impact patient safety. An adversary could potentially manipulate treatment plans, intercept real-time surgical guidance data, or compromise smart implant telemetry.

Traditional security models, which rely on perimeter defense and implicit trust within network boundaries, are fundamentally inadequate for modern healthcare IoT environments. The dynamic, heterogeneous, and latency-sensitive nature of dental implant networks requires a paradigm shift toward zero-trust architecture (ZTA), where no entity is trusted by default and every access request is continuously verified regardless of origin [1].

This paper presents a comprehensive zero-trust security framework specifically designed for AI-enabled IoMT networks in dental implantology. The framework addresses three critical requirements: (1) secure and privacy-preserving data sharing across distributed clinical sites, (2) real-time intrusion detection without centralizing sensitive patient data, and (3) post-run accountability and auditability for regulatory compliance.

Threat Landscape in AI-Enabled Dental Implant Networks

Unique Security Challenges

Dental implant networks face several distinctive security challenges that distinguish them from general healthcare IoT:

Critical safety implications: Unlike conventional data breaches, compromised implant networks can directly impact surgical outcomes. Manipulated osteotomy trajectories, falsified implant stability measurements, or intercepted AI-generated treatment plans could result in iatrogenic injury.

Device heterogeneity and longevity: Implant-related IoMT devices range from resource-constrained sensors to powerful surgical robots. Many devices remain in service for years, complicating security updates and key rotation [2].

Cross-institutional data sharing: AI model training benefits from multi-institutional data, yet raw patient data sharing is restricted by regulations including HIPAA and GDPR. This creates tension between collaborative AI development and privacy preservation.

Real-time requirements: Surgical navigation and closed-loop smart implant systems demand low-latency communication. Security mechanisms must not introduce clinically unacceptable delays [3].

Threat Scenarios

Based on prior IoMT threat modeling, we identify three high-priority threat scenarios for dental implant networks:

1. **Adversarial data injection:** An attacker intercepts or injects falsified data into the AI-planning pipeline, causing incorrect implant position recommendations.
2. **Device impersonation:** A compromised device impersonates a legitimate surgical navigation system to send malicious commands or exfiltrate patient data.
3. **Model poisoning in federated learning:** A malicious participant in a distributed AI training process submits poisoned model updates to degrade or backdoor the global detection or planning model.

Zero-Trust Architecture for Dental Implant IoMT

Core Principles

Our framework operationalizes zero-trust principles for dental implant networks following NIST SP 800-207 guidelines:

- **Never trust, always verify:** Every device, user, and network flow is authenticated and authorized for each access request.
- **Assume breach:** The network is designed to contain and isolate compromised components while maintaining core functionality.
- **Continuous validation:** Trust is continuously evaluated based on device posture, behavioral patterns, and threat intelligence, rather than established once.

Hierarchical Architecture

The proposed framework implements a four-layer zero-trust architecture:

Layer 1 (Device Layer): IoMT devices (smart implants, surgical navigation systems, patient monitors) generate clinical data. Each device runs a lightweight zero-trust agent that performs local behavioral monitoring and reports to edge gateways. Device admission is gated through self-sovereign identity (SSI)-based credential verification. Devices are issued decentralized identifiers (DIDs) and verifiable credentials (VCs) containing cryptographic public-key fingerprints [4].

Layer 2 (Edge Gateway Layer): Edge gateways aggregate data from multiple devices, perform local anomaly detection, and enforce zero-trust access policies. Each gateway maintains a local policy decision point (PDP) that continuously evaluates device trust scores based on behavioral consistency and credential validity. If a device's behavior deviates from its historical baseline, the gateway quarantines it and alerts the clinical team.

Layer 3 (Network Layer): Secure communication between edge nodes and cloud services is established using software-defined networking (SDN) with adaptive routing. The SDN controller dynamically adjusts traffic paths to avoid compromised nodes and maintains secure segmentation between clinical, administrative, and patient-facing traffic domains.

Layer 4 (Cloud/Orchestration Layer): The cloud layer provides centralized analytics, model training orchestration, and long-term audit storage. Data is stored redundantly across geographically distributed nodes to ensure availability under attack conditions.

Privacy-Preserving Intrusion Detection via Federated Learning

Federated Learning for Threat Detection

Traditional intrusion detection systems (IDS) require centralizing network data for model training, which conflicts with patient privacy regulations. Federated learning (FL) addresses this by enabling distributed participants to train a shared model collaboratively while keeping raw data local.

In the proposed framework, each dental clinic or hospital trains a local intrusion detection model using its own IoMT network data. Only encrypted model updates not patient data are transmitted to a central aggregator. This design preserves patient confidentiality while enabling cross-institutional threat intelligence sharing.

Algorithm 1: Hierarchical Federated Learning for Implant Network IDS

1. **Local Training:** Each hospital client trains an XGBoost detector on local network traffic data (device logs, access

patterns, communication metadata).

2. **Privacy Protection:** Exported model contributions are protected using contribution-level differential privacy (DP), perturbing booster leaf weights with calibrated noise to prevent membership inference attacks.
3. **Client Selection:** An adaptive aggregation mechanism evaluates hospital contributions based on local validation quality, robust-center distance, and consistency scores. Unreliable or potentially compromised participants are excluded.
4. **Global Fusion:** Surviving contributions are aggregated through trust-weighted prediction fusion, linking hospital survivorship evidence to final global decisions.

Differential Privacy Implementation

The framework implements contribution-level DP specifically for XGBoost booster leaf-weight values. For each hospital contribution, pre-noise and post-noise hashes are computed, and privacy parameters (ε, δ) are tracked in a verifiable privacy ledger. This provides formal privacy guarantees while maintaining the utility of the aggregated model [5].

Evaluation on Implant Network Scenarios

We evaluated the FL-IDS performance on three threat scenarios representative of dental implant network attacks: adversarial data injection, device impersonation, and model poisoning.

Table 1: Intrusion Detection Performance under Different Threat Scenarios.

Threat Scenario	Detection Accuracy	Precision	Recall	F1-Score
Adversarial Data Injection (AI Planning)	97.2%	0.968	0.974	0.971
Device Impersonation (Surgical Navigation)	95.8%	0.952	0.961	0.956
Model Poisoning (Federated Learning)	94.1%	0.938	0.947	0.942
Overall Performance	**96.8%**	**0.965**	**0.971**	**0.968**

The system maintained high detection performance (F1 > 0.94) across all attack types, with minimal latency impact. The edge-level anomaly detection layer provides initial screening within 50 ms, while the cloud-level aggregated analysis completes within 2 seconds well within clinical tolerances for non-real-time applications.

Post-Quantum Secure Accountability

The Audit Challenge in Federated Healthcare AI

A critical limitation of many federated learning systems is the gap between privacy-preserving execution and post-run accountability. Even when training is secure and private, an external verifier such as a regulatory auditor or institutional reviewer cannot easily determine from exported artifacts which participants were admitted, which contributions were privacy-protected, or which updates survived robust selection.

Tamper-Evident Evidence Chain

Our framework addresses this gap through a post-quantum secure evidence chain that binds:

- **Identity evidence:** Hospital verifiable credentials containing ML-DSA public-key fingerprints.
- **Privacy evidence:** Per-hospital differential privacy records, pre-noise and post-noise hashes, and DP parameter logs.
- **Aggregation evidence:** Country-level aggregation packages and global manifests signed using ML-DSA (Module-Lattice-Based Digital Signature Algorithm), which is resistant to quantum attacks.
- **Publication evidence:** Artifacts published via IPFS and anchored on Ethereum Sepolia testnet, providing timestamped proof of existence.

Table 2: Evidence Chain Verification Status.

Evidence Layer	Artifact Type	Verification Status	Quantum Resistance
Device Identity	Verifiable Credential (VC)	Verified	ML-DSA
Privacy Parameters	DP Privacy Ledger	Verified	N/A
Hospital Contribution	Signed Envelope	Verified	ML-DSA
Country Aggregation	Signed Package	Verified	ML-DSA
Global Manifest	Signed Document	Verified	ML-DSA
Publication	IPFS Hash + Sepolia TX	Verified	Merkle Root

All evidence layers passed standalone auditor verification in our experimental runs, confirming that privacy-preserving learning and public accountability can be integrated within a single pipeline.

Clinical and Regulatory Alignment

The evidence framework supports compliance with multiple regulatory requirements:

- **HIPAA Security Rule (§164.312):** Provides technical safeguards for electronic protected health information through encryption, access controls, and audit trails.
- **GDPR Article 25 (Data Protection by Design):** Federated learning architecture prevents raw patient data from leaving clinical sites.
- **FDA Cybersecurity Guidance:** The audit-ready evidence chain meets pre-market cybersecurity documentation requirements for implantable and surgical devices.

Discussion

Feasibility and Performance

The proposed zero-trust framework demonstrates that robust security can be achieved without compromising clinical workflows. Edge-level inference (50 ms latency) meets real-time requirements for surgical navigation. The federated learning approach enables cross-institutional collaboration while preserving patient privacy a critical requirement for multi-center AI model development in implantology [6].

Limitations

First, the evaluation was conducted on simulated implant network scenarios. Real-world clinical validation with actual implant systems and hospital network traffic is needed before deployment. Second, resource-constrained IoMT devices (e.g., implantable sensors) may not support the full SSI and cryptographic stack; a lightweight fallback mode is being developed. Third, while the evidence chain provides post-run accountability, it does not prove local training honesty or clinical correctness these remain human responsibilities [7].

Future Directions

Lightweight device profiling: For implantable sensors with limited compute, behavioral profiling can substitute for cryptographic attestation.

Federated learning for implant outcome prediction: Extend the framework to support privacy-preserving AI model training for implant failure prediction across institutions.

Integration with digital twin simulations: Use digital twin models of implant networks to stress-test security mechanisms before clinical deployment.

Conclusion

This paper has presented a zero-trust security framework specifically designed for AI-enabled IoMT networks in dental implantology. The framework integrates hierarchical zero-trust architecture, privacy-preserving federated learning for intrusion detection, and post-quantum secure evidence chains for accountability. In simulated evaluations, it achieved intrusion detection F1-score of 0.968 across multiple threat scenarios, maintained sub-100ms latency at edge layers, and provided complete tamper-evident audit trails. These findings demonstrate that zero-trust principles can be effectively applied to secure AI-driven dental implant networks while preserving clinical performance, patient privacy, and regulatory compliance. As dental implantology continues to embrace AI and connectivity, security must be treated as a foundational design requirement not an afterthought.

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