# HIPAA-Compliant Encrypted Medical Chatbot

## Complete Project Plan & Implementation Guide

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## Executive Summary

This document outlines a comprehensive plan for building a HIPAA-compliant, privacy-preserving medical chatbot that enables clinicians to safely query patient Electronic Health Records (EHR) and FHIR data through encrypted vector search. The system combines end-to-end encryption, de-identification, and strict access controls to protect patient data while delivering high-quality clinical decision support. This project is designed for submission to the CyborgDB Healthcare Hackathon, with post-campaign plans for productionization and ecosystem contributions.

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## 1. Project Overview

### Vision

Deliver a secure, privacy-by-design medical AI assistant that allows healthcare clinicians to ask complex clinical questions about patient records without exposing Protected Health Information (PHI) to unauthorized systems, external LLM providers, or database operators.

### Core Innovation

Unlike traditional medical chatbots that expose patient data to third-party APIs or store unencrypted records in standard databases, this solution:

- Generates encrypted embeddings of patient records using domain-specialized medical models
- Stores only ciphertext embeddings in CyborgDB with encryption-in-use
- Decrypts and processes data only in secure backend memory, never persisting plaintext PHI
- Implements HIPAA-mandated access controls, authentication, and comprehensive audit trails

### Key Differentiators

- **End-to-End Encryption**: All data encrypted at rest, in transit, and in-use via CyborgDB
- **De-Identification First**: PHI masking applied before any ML processing
- **Private LLM**: Self-hosted language models eliminate external data transmission
- **Compliance-Ready**: Audit logging, RBAC, and security best practices built in from the start

- **Open Source**: Reference architecture and toolkit published under permissive licenses

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# 2. Objective

## Primary Objective

Create a production-grade prototype of a HIPAA-aligned encrypted medical chatbot that:

1. Safely ingests and de-identifies patient EHR/FHIR data
2. Generates encrypted embeddings using domain-tuned medical transformers
3. Stores encrypted vectors in CyborgDB for privacy-preserving retrieval
4. Answers clinician queries with context-aware responses from a private LLM
5. Maintains comprehensive audit trails and access control logs for compliance verification

## Secondary Objectives

- Benchmark latency, throughput, and resource utilization for encrypted vector search under realistic loads
- Publish open-source integration patterns and documentation for the healthcare community
- Identify CyborgDB limitations, integration pain points, and opportunities for enhancement
- Establish a reference architecture for encrypted healthcare AI that other organizations can build upon

## Success Criteria

- End-to-end chatbot prototype functioning with synthetic FHIR/EHR data
- Query latency <2 seconds for top-k encrypted retrieval + LLM generation
- All data persisted as ciphertext; no plaintext PHI on disk
- Authentication and audit logging functional and tested
- Comprehensive documentation and open-source code released
- Detailed performance benchmarks and CyborgDB integration notes published

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# 3. Workflow & Architecture

## 3.1 Data Ingestion and De-Identification Pipeline

**Stage 1: Data Extraction**

- Source: EHR/FHIR APIs, HL7 feeds, or CSV/JSON dumps (for hackathon: synthetic FHIR datasets)
- Orchestration: Prefect or Apache Airflow
- Frequency: Batch ingestion (daily, weekly) or real-time (via stream processors)
- Output: Raw patient records in standardized format (FHIR JSON)

**Stage 2: PHI Detection and Masking**

- Tools: Presidio, spaCy NER with medical models, transformer-based PHI taggers
- Process:

    - Identify PHI entities: names, addresses, medical record numbers, dates of birth, contact information, social security numbers
    - Mask or tokenize identified entities (e.g., "John Doe" → "[PATIENT_NAME_001]")
    - Preserve clinically relevant dates using relative formats (e.g., "3 days post-op" instead of exact date)
- Output: De-identified FHIR records with clinical content intact

**Stage 3: Validation and Staging**

- Validate de-identified records against FHIR schema
- Store in secure staging area (encrypted cloud storage, secure DB)
- Keep mapping of de-identification tokens in a separate, access-restricted service (not accessible to chatbot)

## 3.2 Embedding Generation and Encrypted Storage

**Stage 1: Embedding Generation**

- Model selection:
    - BioBERT (NCBI pre-trained on biomedical literature)
    - ClinicalBERT (trained on MIMIC clinical notes)
    - PubMedBERT (fine-tuned for medical text)
- Input documents: clinical notes, discharge summaries, lab reports, medication lists, problem lists
- Embedding dimension: typically 768-1024 (model-dependent)
- Process:
    - Batch process de-identified documents through the embedding model
    - Generate one embedding per document or section (configurable granularity)
    - Store metadata: document type, date range, patient pseudonym, encounter ID (all de-identified)

**Stage 2: Client-Side Encryption**

- Encryption algorithm: AES-256-GCM or ChaCha20-Poly1305
- Process:
    - Generate random encryption key for batch
    - Encrypt embeddings (vector + metadata) before transmission
    - Use envelope encryption: encrypt data key with master key stored in AWS KMS / HashiCorp Vault / Azure Key Vault
- Key rotation: Quarterly or upon security event

**Stage 3: CyborgDB Storage**

- Collection schema:
  {
  "patient_id": "pseudo_id_001",
  "encounter_id": "enc_12345",
  "document_type": "discharge_summary",
  "date_range": "2025-01-10_to_2025-01-20",
  "embedding": [encrypted_vector],
  "metadata": [encrypted_metadata],
  "created_at": 1735814400,

"access_log": []
}

- Store only ciphertext; never write plaintext embeddings to disk
- Index on (patient_id, document_type) for efficient filtering during retrieval

### 3.3 Query-Time Workflow

**Step 1: Clinician Authentication**

- Entry: Clinician accesses chatbot web UI
- Auth flow:
  - Redirect to Auth0 / AWS Cognito login
  - MFA verification (optional but recommended)
  - Return JWT access token (valid for 1 hour)
- Validation: Backend verifies JWT signature and checks role (attending, resident, nurse, etc.)

**Step 2: Patient Context Selection**

- Clinician selects or searches for a patient
- Authorization check:
  - RBAC: Does this clinician have permission to access this patient?
  - Relationship check: Is the clinician the treating provider, on the care team, or supervisor?
  - Audit: Log the access attempt (patient ID, clinician ID, timestamp, outcome)
- Output: Patient context loaded (pseudonym, active medications, active problems, recent encounters)

**Step 3: Query Embedding**

- Clinician types question: e.g., "What are the patient's last three eGFR trends and how should we adjust ACE inhibitors?"
- Embedding:
  - Pass question through the same embedding model (BioBERT/ClinicalBERT)
  - Generate query embedding (768-1024 dimensions)
  - Do NOT encrypt query embedding; use plaintext for similarity computation

**Step 4: Encrypted Vector Search in CyborgDB**

- Operation: k-nearest-neighbor (k=5-10) on encrypted vectors
- CyborgDB mechanics:
  - Compute similarity scores over ciphertext (homomorphic encryption or secure MPC)
  - Return top-k encrypted matching embeddings and metadata
  - All computation stays in CyborgDB; plaintext vectors never leave the database
- Latency: Typically 200-500ms for 100K+ encrypted vectors (subject to benchmarking)

**Step 5: In-Memory Decryption and Context Assembly**

- Backend receives encrypted vectors from CyborgDB
- Decrypt in backend process memory (never written to disk):
  - Retrieve decryption key from secure key store

    - Decrypt each embedding's associated metadata (document type, date range, encounter ID)
    - Retrieve corresponding plaintext clinical snippet from secure storage (indexed by encounter ID)
- Assemble context:
  Context for LLM:
    - Patient pseudonym, active medications, active problems, recent labs (de-identified)
    - Top-5 most relevant document snippets (clinical notes, discharge summaries, lab reports)
    - Clinical question from clinician

**Step 6: Private LLM Generation**

- Model: GPT-NeoX-20B, GPT-J-6B, or fine-tuned Llama/Mistral variant
- Deployment: Self-hosted on GPU cluster within healthcare organization's secure environment
- Prompt template:
  You are a clinical decision support assistant. You answer questions based on the patient record provided below.
  Your responses are for clinician review only and do not constitute medical orders or diagnosis.
  Patient Context:
  [pseudonym], age [range], active conditions: [conditions]
  Recent medications: [meds]
  Recent labs: [lab values]
  Relevant Medical Record Excerpts:
  [snippet 1]
  [snippet 2]
  [snippet 3]
  Clinical Question: [question]
  Answer:
- Safety guardrails:
    - Instruction-tuning to refuse requests outside clinical scope
    - Content filters to prevent hallucinations about specific drugs/doses
    - Mandatory disclaimers: "This is decision support, consult pharmacy/attending before prescribing"
    - Response truncation if exceeds safe length (~500 words)

**Step 7: Response Logging and Return**

- Log interaction:
  {
  "clinician_id": "MD_12345",
  "patient_pseudo_id": "patient_001",
  "timestamp": 1735814400,
  "query_text": "What are last three eGFR trends?",
  "retrieved_documents": 5,
  "response_tokens": 120,
  "response_text": "[GENERATED ANSWER]",
  "outcome": "success"
  }

- Return answer to clinician UI with:
  - Generated clinical response
  - Links to source documents (de-identified titles and dates)
  - Explicit disclaimer about decision support nature
  - Option to flag response for pharmacist/attending review

## 3.4 Security, Access Control, and Auditing

**Authentication & Authorization**

- Identity provider: Auth0 or AWS Cognito
- MFA: Email OTP or TOTP-based (authenticator app)
- Session: JWT tokens, 1-hour expiry, refresh tokens with longer TTL
- RBAC:
  - Roles: Attending Physician, Resident, Nurse, Pharmacist, QA/Audit
  - Scopes: patient-read, patient-query, audit-log-read, admin-config
  - Per-patient access checks enforced on every query

**Encryption**

- Data at rest: AES-256-GCM for all stored embeddings and logs
- Data in transit: TLS 1.3 for all API calls
- Key management:
  - Master keys in AWS KMS / Azure Key Vault / HashiCorp Vault
  - Key rotation: Quarterly or on-demand
  - Key access: Limited to authenticated backend service account only

**Audit Logging**

- Immutable append-only log (database or write-once storage)
- Log entries include:
  - Timestamp, user ID, action (login, query, retrieve document, modify access)
  - Patient pseudonym, resource ID
  - Result (success/failure) and any error details
  - IP address and user agent (for anomaly detection)
- Retention: Minimum 6 years (HIPAA requirement)
- Access: Only authorized compliance/audit staff can read audit logs

**Network & Infrastructure**

- VPC/network isolation: Chatbot API, LLM, CyborgDB, and key stores in same VPC
- No direct internet access for PHI; egress only through authenticated proxies
- Secrets management: No credentials hardcoded; all injected via secure secrets engine
- Regular updates: Patch OS, libraries, and dependencies monthly

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## 4. Comprehensive Tech Stack

### 4.1 Data Pipeline and Orchestration

| Tool/Library | Version | Purpose | How to Use |
|---|---|---|---|
| **Apache Airflow** or **Prefect** | 2.x | Workflow orchestration for EHR ingestion, PHI masking, embedding generation | Define DAGs (Airflow) or flows (Prefect) with tasks for data extraction, validation, PHI masking, and storage. Schedule daily/weekly runs. Monitor via web UI. |
| **Presidio** | 2.x | PII/PHI detection and anonymization | Apply Presidio analyzers and anonymizers to detect entities (names, IDs, dates) and mask them. Integrate into Airflow task. |
| **spaCy** | 3.x | NLP and named entity recognition | Load medical NER models; use for additional PHI detection (clinical concepts, medications). Chain with Presidio for multi-stage masking. |
| **Pandas & Polars** | Latest | Data manipulation and transformation | Read FHIR JSON, manipulate tables, prepare batches for embedding generation. |
| **Cryptography / PyCryptodome** | Latest | Encryption utilities | Implement AES-256-GCM encryption for embeddings before CyborgDB storage. |

### 4.2 Embeddings and Language Models

| Model/ Tool | Source | Purpose | How to Use |
|---|---|---|---|
| **BioBERT** | Hugging Face (monologg/biobert-base-cased-v1.1) | Medical text embeddings | Load pre-trained model, encode de-identified clinical notes into 768-dim vectors. |
| **ClinicalBERT** | Hugging Face (emilyalsentzer/clinicalbert) | MIMIC-trained clinical embeddings | Alternative to BioBERT; trained specifically on clinical note corpus. Use for domain specificity. |
| **PubMedBERT** | Hugging Face (microsoft/pubmedbert-base) | Biomedical literature embeddings | For research-heavy queries; trained on PubMed abstracts and full texts. |
| **GPT-NeoX-20B** or **GPT-J-6B** | EleutherAI / Hugging Face | Private LLM for answer generation | Deploy on GPU cluster; run inference with prompt template. Avoid external API calls. |
| **Llama 2** / **Mistral** | Meta / Mistral AI | Alternative private LLMs | Lightweight, fine-tunable alternatives. Can deploy on smaller GPUs. |
| **Hugging Face Transformers** | 4.x | Loading and running models | from transformers import AutoModel, AutoTokenizer; model = AutoModel.from_pretrained(...); embeddings = model(...).last_hidden_state.mean(dim=1) |

### 4.3 Encrypted Vector Search

| Tool | Version | Purpose | How to Use |
|---|---|---|---|
| **CyborgDB SDK** | Latest | Encrypted vector database | Create collection, insert encrypted embeddings, run k-NN search over ciphertext. Example: `cyborg_db.insert(patient_id, encrypted_embedding, metadata)` and `results = cyborg_db.search(query_embedding, k=10)` |
| **CyborgDB Encryption Module** | Built-in | Encryption-in-use for vectors | Use homomorphic encryption or secure MPC provided by CyborgDB; configure key derivation and rotation policies. |
| **AWS KMS** or **Vault** | Latest | Master key management | Store encryption keys; integrate with backend to retrieve keys for de-encryption. Rotate quarterly. |

### 4.4 Backend API and Integration

| Framework/Tool | Version | Purpose | How to Use |
|---|---|---|---|
| **FastAPI** | 0.95+ | REST API framework | Define Pydantic models for request/response, create async endpoints for /login, /patients, /ask-question, /audit-log. Use dependency injection for auth middleware. |
| **Flask** | 2.x | Alternative lightweight framework | Use if FastAPI is overkill; build routes for same endpoints. |
| **FHIR Client (fhirpy)** | Latest | FHIR API integration | Connect to EHR FHIR servers to pull synthetic/real patient data. Example: `client = AsyncFHIRClient('https://fhir.example.com'); patients = await client.resources('Patient').fetch()` |
| **Python-Jose** or **PyJWT** | Latest | JWT handling | Parse and validate access tokens from Auth0/Cognito. Implement custom claims checks for RBAC. |
| **SQLAlchemy** | 2.x | ORM for logging database | Define models for audit logs, user sessions, and access control rules. |
| **Pydantic** | 2.x | Data validation | Define schemas for API requests, responses, and audit log entries. Enforce types and constraints. |

### 4.5 Authentication and Authorization

| Service/Tool | Purpose | How to Use |
|---|---|---|
| **Auth0** | Identity provider (SaaS) | Create Auth0 tenant, configure social/email login, set up MFA, define roles and permissions, issue JWTs. Integrate via OAuth 2.0 / OpenID Connect. |
| **AWS Cognito** | Alternative identity provider (AWS-native) | Create user pool, configure MFA, define custom attributes, generate tokens. Integrate via Cognito SDK or OIDC. |
| **FastAPI Security Dependencies** | Role-based access control in API | Use `Depends(verify_jwt)` to validate tokens on protected routes; check role claims for RBAC. |

### 4.6 Logging and Audit

| Tool | Version | Purpose | How to Use |
|---|---|---|---|
| **Python logging** | Built-in | Structured logging | Define handlers for console/file; use JSON formatter for structured logs. Log all access events, queries, errors. |
| **ELK Stack (Elasticsearch, Logstash, Kibana)** | Latest | Log aggregation and visualization | Ship JSON logs to Elasticsearch; visualize in Kibana dashboards. Ideal for audit log analysis. |
| **AWS CloudWatch** | Latest | Cloud-native logging | Send logs to CloudWatch; set up alarms for suspicious access patterns. |
| **PostgreSQL** or **SQLite** | Latest | Audit log persistence | Store logs in database with encrypted sensitive fields. Use immutable/append-only tables for compliance. |

### 4.7 Frontend

| Framework | Version | Purpose | How to Use |
|---|---|---|---|
| **React** or **Next.js** | 18+ | Web UI for clinicians | Build pages: login, patient selector, chat interface, answer display, audit log viewer. Use React Query for data fetching. |
| **Tailwind CSS** or **Material-UI** | Latest | Styling | Responsive design, accessibility (WCAG 2.1 AA), dark mode support. |
| **Web-based UI** (minimal) | - | For hackathon MVP | Simple HTML/JavaScript with fetch API; no heavy framework overhead. |

### 4.8 Deployment and Infrastructure

| Tool | Purpose | How to Use |
|---|---|---|
| **Docker** | Containerization | Package backend API, embedding service, LLM, and supporting tools in separate containers. Use docker-compose for local dev; Kubernetes for production. |
| **Kubernetes** | Orchestration | Deploy backend replicas, stateful CyborgDB pods, GPU-enabled LLM inference nodes. Use Helm for templating and versioning. |
| **AWS ECS / EKS** or **Azure Kubernetes Service** | Managed container platforms | Simpler alternative to self-managed Kubernetes. Supports encrypted storage, network policies, and HIPAA-aligned compliance frameworks. |
| **Terraform** | Infrastructure-as-Code | Define VPC, subnets, security groups, KMS keys, RDS (for audit logs), container registries. Version control infrastructure. |

### 4.9 Testing and Benchmarking

| Tool | Purpose | How to Use |
|---|---|---|
| **pytest** | Unit and integration testing | Write tests for API endpoints, encryption/decryption, PHI masking, LLM response generation. |
| **Locust** or **Apache JMeter** | Load testing | Simulate concurrent clinicians querying the chatbot; measure latency, throughput, error rates under encrypted search. |
| **Profiling tools (py-spy, cProfile)** | Performance analysis | Identify bottlenecks in embedding generation, CyborgDB search, and LLM inference. |

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## 5. Implementation Roadmap

### Phase 1: Foundation (Weeks 1-2)

**Deliverables:**

- Synthetic FHIR dataset (100-500 patient records with clinical notes, labs, medications)
- PHI masking pipeline (Presidio + spaCy) tested on sample data
- De-identification validation script
- Local development environment (Docker Compose setup)

**Key Tasks:**

1. Generate or download synthetic FHIR data (e.g., from Synthea)
2. Implement PHI detection using Presidio and medical NER
3. Test masking on sample records; verify no PHI leakage
4. Containerize data pipeline

### Phase 2: Embeddings and Vector Storage (Weeks 2-3)

**Deliverables:**

- Embedding generation script for clinical documents
- Encrypted embeddings stored in CyborgDB
- Encryption/decryption utilities tested
- Performance benchmarks for embedding generation (docs/sec, memory usage)

**Key Tasks:**

1. Load BioBERT/ClinicalBERT models

2. Batch process de-identified clinical notes → embeddings
3. Encrypt embeddings using AES-256-GCM
4. Insert encrypted vectors into CyborgDB with metadata
5. Benchmark: 1000 docs → X seconds, Y MB memory
6. Document CyborgDB SDK integration notes

### Phase 3: Backend API and LLM Integration (Weeks 3-4)

**Deliverables:**

- FastAPI backend with endpoints: /login, /patients, /ask-question, /audit-log
- Auth0/Cognito integration
- Private LLM integration (GPT-NeoX or GPT-J)
- Prompt templates and safety guardrails

**Key Tasks:**

1. Implement JWT validation and RBAC checks
2. Build /ask-question endpoint: query embedding → CyborgDB search → in-memory decryption → LLM call
3. Deploy private LLM on GPU cluster or local GPU
4. Test end-to-end workflow with sample queries
5. Add response disclaimers and safety filters
6. Implement structured logging for audit trail

### Phase 4: Frontend and Testing (Week 4)

**Deliverables:**

- Clinician web UI (login, patient selector, chat interface)
- Integration tests and load tests
- Performance benchmarks (query latency, throughput)
- Documentation and open-source release

**Key Tasks:**

1. Build React/Next.js or minimal HTML UI
2. Integrate with backend API
3. Write pytest unit tests for core functions
4. Run Locust load tests; measure latency/throughput under encrypted search
5. Generate performance report: latency vs. dataset size, throughput, resource usage
6. Prepare GitHub repository with README, setup instructions, and benchmark results

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# 6. Expected Impacts

## 6.1 Privacy and Compliance Impact

- **HIPAA Risk Reduction**: Encrypted-at-rest, in-transit, and in-use prevents unauthorized PHI exposure. Comprehensive audit trails satisfy technical safeguard requirements.
- **Breach Prevention**: Even if CyborgDB is compromised, attackers obtain only ciphertext. Decryption keys remain in secure key management service.

- **Regulatory Confidence**: Clear documentation of security controls facilitates compliance audits, BAA negotiations, and regulatory submissions.

### 6.2 Clinical Impact

- **Faster Clinical Decision Making**: Clinicians can instantly retrieve relevant patient history and evidence-based guidance, reducing chart review time by 30-50%.
- **Improved Patient Safety**: Decision support reduces medication errors and improves guideline adherence.
- **Reduced Documentation Burden**: Automated summarization of long notes saves administrative time.

### 6.3 Organizational Impact

- **Operational Efficiency**: Reduced manual chart searches, faster patient reviews, and less time spent on administrative queries.
- **Competitive Advantage**: Healthcare organizations deploying privacy-preserving AI attract top clinical and technical talent.
- **Data Monetization Opportunity**: De-identified, encrypted data can be securely shared with researchers without compliance friction.

### 6.4 Technology and Open-Source Impact

- **Reference Architecture**: Establishes a gold-standard pattern for encrypted healthcare AI that others can adopt.
- **CyborgDB Validation**: Demonstrates production viability of encrypted vector search for healthcare use cases; provides integration feedback.
- **Community Contributions**: Open-source code, tutorials, and benchmarks accelerate healthcare AI research and deployment across organizations.

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## 7. Post-Campaign Roadmap

### 7.1 Months 1-3: Productionization

- **Compliance hardening**:
  - Formal HIPAA risk assessment with security/compliance teams
  - Business Associate Agreements (BAAs) with CyborgDB, cloud providers
  - Incident response playbook and security training for clinical staff
- **Access control refinement**:
  - Granular RBAC: attending-only, resident-supervised, patient-relationship checks
  - Audit log dashboards for compliance officers
- **Model optimization**:
  - Fine-tune embedding models on institution-specific clinical notes
  - Reduce embedding latency via quantization and distillation
  - Benchmark alternative LLMs (Llama, Mistral) for speed/quality tradeoff

### 7.2 Months 4-6: Feature Expansion

- **Hybrid retrieval**:
  - Add encrypted keyword search (BM25 over encrypted indexes)
  - Combine vector search with structured queries on FHIR elements (labs, medications)
- **Extended use cases**:
  - Patient-facing education flows (discharge instructions, medication adherence reminders)
  - Automated clinical note summarization
  - Drug-drug interaction screening
  - Sepsis/deterioration risk alerts
- **EHR integrations**:
  - FHIR API connectors for major EHR vendors (Epic, Cerner, Athena)
  - HL7 v2 gateways for legacy systems
  - CDS Hooks integration for in-workflow decision support

### 7.3 Months 7-12: Scaling and Ecosystem

- **Multi-site deployment**:
  - Deploy to 3-5 health systems; collect real-world performance and clinical feedback
  - Standardize deployment playbooks and Terraform modules
- **Community engagement**:
  - Publish monthly blog posts on encrypted healthcare AI
  - Host webinars on CyborgDB integration and HIPAA compliance
  - Accept community contributions to open-source toolkit
- **Research partnerships**:
  - Collaborate with academic medical centers on model fine-tuning
  - Publish peer-reviewed papers on privacy-preserving clinical AI
  - Open dataset: de-identified queries and synthetic FHIR records for ML research

### 7.4 Year 2+: Commercialization and Standards

- **Commercialization paths**:
  - Offer managed service (SaaS) or self-hosted licenses
  - Consulting services for health systems integrating encrypted AI
- **Standards development**:
  - Contribute to HL7 security and privacy working groups
  - Advocate for HIPAA-aligned requirements in AI governance frameworks
  - Promote encryption-in-use as industry best practice

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## 9. Conclusion

This HIPAA-compliant encrypted medical chatbot represents a significant step forward in combining clinical AI with privacy-by-design principles. By leveraging CyborgDB's encryption-in-use capabilities, domain-specialized medical models, and strict access controls, the project delivers a system that clinicians and patients can trust both for security and clinical quality.

The four-week development roadmap is ambitious but achievable, with clear milestones and open-source deliverables. Post-campaign expansion focuses on productionization, regulatory alignment, and ecosystem contributions that will establish this architecture as the gold standard for privacy-preserving healthcare AI.

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## Appendix A: Sample Configuration Files

### A.1 Docker Compose (Development)

```
version: '3.8'
services:
backend:
build: ./backend
ports:
- "8000:8000"
environment:
```

```
- DATABASE_URL=postgresql://user:password@postgres:5432/audit_db
- CYBORG_DB_URL=cyborg://cyborg-db:5432
- AUTH0_DOMAIN=your-tenant.auth0.com
- AUTH0_CLIENT_ID=your-client-id
- KMS_ENDPOINT=http://kms-service:9000
depends_on:
- postgres
- cyborg-db

postgres:
image: postgres:15
environment:
- POSTGRES_USER=user
- POSTGRES_PASSWORD=password
- POSTGRES_DB=audit_db
volumes:
- postgres_data:/var/lib/postgresql/data

cyborg-db:
image: cyborgdb/encrypted-vector-db:latest
ports:
- "5432:5432"
environment:
- ENCRYPTION_MODE=HOMOMORPHIC
volumes:
- cyborg_data:/data

llm-service:
image: llm/gpt-neox-20b:latest
ports:
- "8001:8000"
volumes:
- model_cache:/models

volumes:
postgres_data:
cyborg_data:
model_cache:
```

### A.2 FastAPI Backend (Skeleton)

```
from fastapi import FastAPI, Depends, HTTPException
from fastapi.security import OAuth2PasswordBearer
import jwt
from datetime import datetime
import logging

app = FastAPI()
oauth2_scheme = OAuth2PasswordBearer(tokenUrl="login")
```

# Structured logging

logging.basicConfig(format='%(asctime)s - %(name)s - %(levelname)s - %(message)s')
logger = logging.getLogger(**name**)

@app.post("/login")
async def login(username: str, password: str):
"""Authenticate user via Auth0 and return JWT."""
# Validate credentials against Auth0
# Return JWT access token
logger.info(f"Login attempt for user {username}")
pass

@app.get("/patients")
async def get_patients(token: str = Depends(oauth2_scheme)):
"""Retrieve list of patients accessible to authenticated clinician."""
# Validate JWT
# Check RBAC
# Query patient list from secure store
logger.info(f"Patient list retrieved for authenticated user")
pass

@app.post("/ask-question")
async def ask_question(patient_id: str, question: str, token: str = Depends(oauth2_scheme)):
"""Main query endpoint: embedding → CyborgDB search → LLM generation."""
# 1. Validate JWT and RBAC
# 2. Generate question embedding
# 3. Query CyborgDB (encrypted search)
# 4. Decrypt retrieved embeddings in memory
# 5. Call private LLM
# 6. Log interaction
# 7. Return response

```
logger.info(f"Query received: patient={patient_id}, question={question[:50]}...")

# [Implementation details...]

return {"response": "Clinical answer here", "sources": [...]}
```

@app.get("/audit-log")
async def get_audit_log(token: str = Depends(oauth2_scheme)):
"""Retrieve audit log entries (compliance officers only)."""
# Verify user has audit-log-read scope
# Return paginated audit log
logger.info(f"Audit log accessed")
pass

---

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