AI Health Coach Architecture (v1.0)

Production-Grade, Safety-First Healthcare AI — From Wearables to Escalation

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This white paper translates the AI Health Coach architecture into an implementable, safety-first blueprint. It focuses on system design choices that reduce clinical risk: separation of concerns (ML vs. LLM vs. evidence), guardrails that override “helpful” language, and operational controls that make the system auditable in production.

Executive Summary

Healthcare is still largely reactive: symptoms appear, care is delayed, and conditions escalate. Yet continuous early signals—heart rate, blood pressure, sleep quality, oxygen saturation, lab trends—are already available through wearables and home devices. The missing layer is not data collection; it’s responsible, continuous interpretation.

The AI Health Coach is designed as a decision-support system, not a “medical chatbot.” It combines three distinct engines:

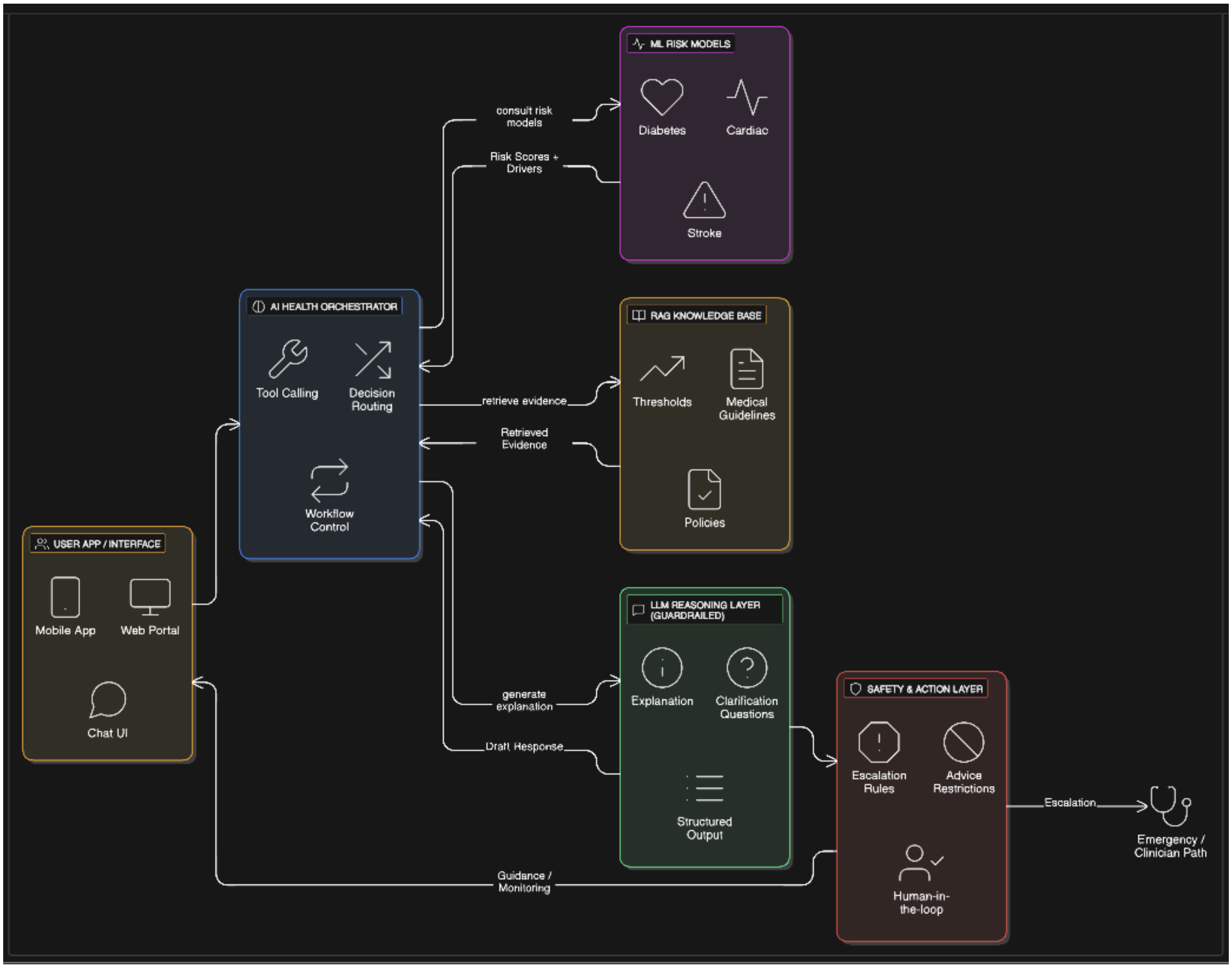
- **Predict risk with ML:** disease-specific models produce risk bands, confidence, and contributing factors from structured signals.
- **Ground recommendations with retrieval (RAG):** the system retrieves approved thresholds, clinical guidelines, and policies before the LLM speaks.
- **Explain with constrained LLM output:** the LLM translates risk + evidence into human-readable guidance, asks clarifying questions, and never diagnoses.

Safety is enforced through deterministic rules, escalation pathways, and comprehensive audit logging. When risk crosses predefined thresholds—or when uncertainty is high—the system stops “chatting” and routes users into an emergency or clinician path. Production readiness is treated as core architecture: model registry, monitoring for drift and calibration, cost/latency observability, and privacy-by-design controls.

The outcome is a scalable blueprint that can start as a controlled triage assistant and expand into a multi-disease platform over time—without rebuilding the entire system for each new condition.

Architecture at a Glance

The system is intentionally modular. Each module has a single responsibility, and the orchestrator governs the workflow. This separation is what enables safety, auditability, and long-term scalability.



Key design rule: the LLM is the communicator, not the decision-maker. Risk is computed by ML, evidence is retrieved from controlled sources, and the safety layer can block, redirect, or escalate regardless of how “confident” the LLM sounds.

1. Problem Framing: Why Reactive Healthcare Fails

Most healthcare journeys follow the same failure mode: symptoms appear, the patient delays seeking care, and the condition escalates. This is rarely a clinical competence problem—it's a timing problem. Signals exist earlier than clinical visits, but nobody interprets them continuously.

A deployable AI Health Coach does not claim to replace clinicians. Its job is narrower and more practical: connect early signals into a risk-aware narrative, explain what is happening in plain language, and route the user to the next safe action.

2. Multi-Source Health Data: Context Beats Any Single Signal

The system contextualizes health signals across five categories. The same symptom can mean different things for different people; context is what prevents unsafe generalization.

- **Past medical history:** existing conditions, medications, family history.
- **Labs and reports:** glucose/lipids/CBC, ECG summaries, clinician notes (structured extracts).
- **Real-time wearables:** heart rate, blood pressure, SpO■, sleep, activity, HRV (when available).
- **Live symptoms:** user-reported symptoms captured in structured forms plus short free-text.
- **Clinical knowledge base:** approved thresholds, guidelines, and internal safety policies.

The orchestrator normalizes and validates these inputs before any downstream component runs. This is a deliberate stance: we do *not* feed raw, noisy, multi-source data blindly into an LLM.

3. Predictive Engine: Multi-Disease ML Risk Platform

Risk estimation is handled by disease-specific ML models—diabetes first, then cardiac, stroke, and hypertension as the platform expands. A single “one model for everything” approach is brittle in healthcare because feature meaning and acceptable error differ by condition.

Each model produces more than a label. It outputs:

- **Risk band or probability** (e.g., low/medium/high with calibrated thresholds).
- **Confidence/uncertainty** so the system can avoid false reassurance.
- **Top contributing factors** that explain what signals drove the risk.

These outputs are versioned and monitored in production. When risk scores drift, the platform must be able to answer: which model ran, which data influenced the result, and what changed compared to prior behavior.

4. Trust Layer: Retrieval-Augmented Generation (RAG)

In healthcare, trust collapses when an assistant is confident but wrong. RAG is the system’s defense against hallucination and policy drift. Before generating guidance, the system retrieves evidence from a curated knowledge base containing thresholds, guidelines, and policies.

- **Grounding:** responses must be supported by retrieved content, not model memory.
- **Citations and traceability:** each safety-relevant claim can be linked back to a document, version, and section.
- **Governance:** knowledge can be permissioned and region-specific (hospital policy, payer rules, local regulations).

5. Reasoning Layer: Guardrailed LLM for Explanation, Not Authority

Only after risk and evidence are prepared does the system invoke the LLM. The LLM translates structured outputs into human language, asks clarifying questions when input data is incomplete, and formats responses into a structured template (signals → meaning → action).

Crucially, the LLM is constrained by: (1) retrieved evidence, (2) refusal and escalation policies, and (3) deterministic guardrails that can override generation. This keeps the system aligned with decision support rather than diagnosis or treatment.

6. Safety & Governance: A “Do No Harm” Architecture

Safety is not a prompt. It is enforced through layered controls that assume components can fail. The system uses four pillars that reduce the chance of harm and increase accountability:

- **Human-in-the-loop escalation:** high-risk outputs route to clinician or emergency pathways rather than open-ended conversation.
- **Deterministic guardrails:** hard rules restrict unsafe advice and force “I don’t know” or “seek urgent care” when appropriate.
- **Comprehensive audit logs:** inputs, model versions, retrieved evidence, fired rules, and final output are logged for investigation and compliance.
- **Privacy by design:** least-privilege access, encryption in transit/at rest, and minimized PHI exposure across services.

7. Engineered for Production: MLOps & Observability

Production is operations. The platform is designed to remain reliable after deployment through reproducible pipelines, experiment tracking, a model registry with promotion gates, structured logging, and monitoring across four dimensions: performance (including calibration), data drift, safety incidents, and cost/latency.

8. Phased Deployment & Measurable Impact

Phase 1 (MVP validation): a controlled pilot using a lightweight web interface validates end-to-end workflow, safety triggers, and explanation quality. Models and knowledge sources are tuned with internal users before broader exposure.

Phase 2 (scale to users): a native mobile app connects to hardened APIs deployed on managed Kubernetes with secrets management, RBAC, and encrypted storage. Rollout is incremental, with monitoring-driven gates.

When executed well, the system delivers enterprise outcomes: fewer avoidable emergencies through earlier escalation, reduced load on clinics via better triage, and improved patient adherence because guidance is clear, evidence-based, and time-bound.

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