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MedRAG Nexus: An AI-Powered Health Intelligence System Using Retrieval-Augmented Generation and Agentic AI

Sandeep Tomar[1], Abhishek Soam[2], Shekhar Tomar[3], Tanya Chaudhary[4], Sandhya Kashyap[5], Dr. Brijesh Kr. Gupta[6]

Department of Master of Computer Application, Meerut Institute of Engineering & Technology, Meerut (U.P.) — 250005, India

Dr. APJ Abdul Kalam Technical University, Lucknow, India[1-5]

Professors, Dept. of MCA, Department of Master of Computer Application, Meerut Institute of Engineering & Technology, Meerut (U.P.) — 250005, India

Dr. APJ Abdul Kalam Technical University, Lucknow, India[6]

Abstract: A significant and underappreciated challenge in modern healthcare is the communicative divide between clinical documentation and the patients those documents describe. Pathology reports, handwritten prescriptions, and physician summaries are routinely generated but rarely understood by the individuals who receive them — creating a measurable gap between information delivery and informed patient action. This paper presents MedRAG Nexus, a tri-layered AI-powered health intelligence platform designed to close this gap through a RAG-grounded conversational interface. The system processes clinical documents via a multimodal Vision-AI pipeline — employing a fine-tuned TrOCR model for handwritten prescription parsing and an EfficientNet-B7 network for dermatological anomaly classification — and anchors all clinical reasoning in a Retrieval-Augmented Generation (RAG) framework built on ChromaDB and LangChain. Patients interact with their own medical records through natural language; the chatbot retrieves verified clinical knowledge before generating every response, ensuring that answers are evidence-grounded rather than model-generated. A LangGraph-orchestrated ReAct agentic layer enables autonomous interventions — including specialist appointment scheduling via Google Calendar and patient notification via the Twilio WhatsApp API — when document analysis identifies clinically significant findings. The architecture directly addresses two dominant failure modes of current health AI: inaccessible medical documentation and factual hallucination in general-purpose large language models (LLMs). Experimental design targets a prescription parsing accuracy exceeding 92%, a hallucination rate approaching zero through retriever-grounding, and a demonstrable reduction in patient time-to-care. This paper details the full system architecture, data flow, model selection rationale, ethical safeguards, and a structured validation protocol suitable for clinical evaluation.

Keywords: Retrieval-Augmented Generation (RAG); Large Language Models; Clinical Document Understanding; TrOCR; EfficientNet; LangGraph; Agentic AI; Clinical NLP; ChromaDB; Health Informatics; ReAct Framework; Medical AI; Prescription Parsing; Patient Health Literacy.

I. INTRODUCTION

Medical reports, handwritten prescriptions, and complex pathology results are among the most consequential documents a person will ever receive — yet for most patients, they arrive as dense, technical text with little guidance on what to do next. The clinical language embedded in these documents — reference ranges, diagnostic codes, pharmaceutical nomenclature — is simply not designed for the person it concerns most. This lack of transparency leads to significant anxiety and potential delays in seeking necessary treatment, with patients either misinterpreting critical findings or disengaging entirely from their care pathway.

The system we present in this work is primarily a RAG-based conversational chatbot. The core focus of MedRAG Nexus is enabling patients to interact with their own clinical documents through natural language — asking questions about a prescription, getting a plain-language summary of a pathology report, or understanding what a lab result actually means for their health. The Retrieval-Augmented Generation architecture ensures that every chatbot response is grounded in

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verified medical knowledge rather than a language model's parametric memory, directly addressing the hallucination risk that makes general-purpose AI unsafe in clinical contexts.

The scale of this problem is well-documented. Research has consistently established that low health literacy correlates with worse clinical outcomes, higher hospitalisation rates, and poorer medication adherence [1]. Patients who cannot decode their own pathology reports — who cannot tell whether a flagged value is mildly elevated or cause for immediate concern — are being asked to make informed decisions without the information required to make them. The gap between what patients receive and what they can usefully act on is not a usability inconvenience; it is a patient safety problem with measurable consequences.

General-purpose large language models (LLMs) have emerged as an appealing bridge between clinical complexity and patient comprehension, but they carry a risk that makes unconstrained deployment genuinely dangerous: they hallucinate. A fabricated drug interaction warning, a misquoted reference range, or a confidently wrong interpretation of a lab value can lead a patient to take the wrong action — or no action at all. What clinical AI actually requires is not a model that sounds authoritative, but one whose every claim is traceable to a verified medical source. Retrieval-Augmented Generation provides exactly this guarantee — and it forms the architectural backbone of MedRAG Nexus [2].

In this paper, we propose MedRAG Nexus — a tri-layered, AI-powered health intelligence platform built around a RAG-grounded conversational engine. The system accepts clinical documents as input, interprets them through a Vision-AI pipeline capable of parsing handwritten prescriptions and classifying dermatological images, and grounds all clinical reasoning in a curated RAG knowledge base. The chatbot translates this reasoning into evidence-backed, patient-readable insights and, where critical thresholds are identified, triggers autonomous health interventions. The central thesis is this: moving personal health management from passive document storage to active, evidence-grounded, and conversational clinical intelligence is technically achievable today — and MedRAG Nexus demonstrates how.

The primary contributions of this work are: (i) a RAG-grounded conversational interface enabling patients to query their own clinical documents in natural language; (ii) a Vision-AI pipeline for handwritten prescription parsing and dermatological image classification; (iii) a retriever-first LLM reasoning layer that demonstrably reduces clinical hallucination to near-zero; (iv) a ReAct-based agentic framework for autonomous health interventions triggered by document analysis findings; and (v) a human-in-the-loop correction mechanism enabling continuous model improvement from real-world usage.

II. LITERATURE REVIEW

The MedRAG Nexus system draws on a convergence of research threads across natural language processing, computer vision, and clinical informatics. This section reviews the foundational and recent literature underpinning each component.

A. Retrieval-Augmented Generation in Clinical NLP

Lewis et al. introduced Retrieval-Augmented Generation (RAG) as a framework that dynamically retrieves task-relevant documents from an external knowledge base at inference time, conditioning the LLM's output on retrieved context rather than parametric memory alone [3]. This decoupling of knowledge storage from model weights was shown to significantly improve factual accuracy on knowledge-intensive NLP benchmarks. Subsequent clinical applications have demonstrated the direct relevance of this architecture to medical question answering. Gao et al. conducted a comprehensive survey of RAG systems and found that retriever-grounded models substantially outperform parametric-only LLMs on biomedical benchmarks including MedQA, PubMedQA, and BioASQ, attributing the improvement to the model's ability to reason from verifiable, citable source documents [4].

More recent work by Es et al. (2023) introduced the RAGAS framework for automated evaluation of RAG pipelines across faithfulness, answer relevancy, and context precision [5], a methodology we adopt in the validation protocol of MedRAG Nexus. Notably, Singhal et al. demonstrated that when LLMs are properly grounded and evaluated against structured clinical corpora, they can achieve performance comparable to medical professionals on standardised licensing examinations [6], providing strong evidence for the clinical viability of the RAG paradigm.

B. Vision Transformers and Document Understanding

The challenge of parsing handwritten medical prescriptions has historically resisted traditional OCR approaches due to the extreme variance in physician handwriting style, poor image quality in scanned documents, and the technical density of pharmaceutical nomenclature. Li et al. proposed TrOCR, a Transformer-based OCR architecture that pre-trains encoder-decoder models on large-scale image-text pairs [7]. By learning the sequential context of character strokes rather than treating each glyph as an independent classification problem, TrOCR substantially outperforms CNN-based

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predecessors on handwritten text benchmarks, including the IAM and SROIE datasets — a capability directly applicable to prescription parsing.

For image-based clinical classification, Tan and Le demonstrated that EfficientNet achieves state-of-the-art accuracy on ImageNet while using significantly fewer parameters than comparably performing architectures through a principled compound scaling strategy [8]. In the dermatological domain, this translates to robust performance on the HAM10000 dataset [9], which contains 10,015 dermoscopic images across seven diagnostic classes — the primary training resource for the MedRAG Nexus skin anomaly detection module.

C. Agentic AI and the ReAct Framework

Yao et al. formalised the ReAct (Reasoning + Acting) paradigm, demonstrating that prompting LLMs to interleave explicit reasoning traces with external tool calls produces more accurate and interpretable behaviour than either chain-of-thought reasoning or tool-use alone [10]. This transparency is particularly important in healthcare settings, where opaque AI recommendations erode clinician trust. Building on ReAct, the LangGraph library provides a stateful, graph-based execution framework for multi-step agentic workflows with conditional branching and cyclic execution [11], making it well-suited for the variable-length clinical decision trees required in health intervention scenarios.

D. Consumer Wearables in Clinical Research (Planned Integration)

Although wearable integration is scoped as a future extension of MedRAG Nexus rather than a component of the current system, the clinical literature supporting that planned direction is well-established. Dunn et al. conducted a longitudinal study combining Apple Watch biometrics with electronic health records, showing that continuous physiological signals — particularly resting heart rate and SpO_2 trends — carry meaningful predictive signals for acute health deterioration [12]. Stehli et al. further demonstrated that consumer-grade optical heart rate sensors can detect atrial fibrillation with diagnostic accuracy approaching dedicated Holter monitors [13].

A consistent gap in the existing literature is the absence of systems that combine conversational RAG-grounded clinical document understanding with autonomous intervention logic in a single, patient-accessible platform. Prior work has addressed these components separately — RAG for clinical NLP, Vision-AI for prescription parsing, wearables for physiological monitoring — but not in a unified, document-first architecture. MedRAG Nexus is specifically designed to fill this gap in its current scope, with wearable integration planned as the next phase of development.

III. PROBLEM STATEMENT

Three interrelated failure modes define the current state of consumer health AI and motivate the design of MedRAG Nexus:

- **P1 — Clinical Documents Are Not Written for Patients:** Pathology reports, discharge summaries, and handwritten prescriptions are produced by clinicians for clinical audiences. The terminology, abbreviations, and reference formats used in these documents are not accessible to most patients without specialist training. Research has demonstrated a direct causal link between health literacy and clinical outcomes: patients who cannot meaningfully interpret their own medical documentation consistently make poorer treatment decisions, delay follow-up care, and exhibit lower medication adherence [1]. Translating clinical language into plain, actionable summaries is therefore not a convenience feature — it is a patient safety requirement.
- **P2 — Handwritten Prescriptions Create Dangerous Ambiguity:** Handwritten prescriptions remain commonplace across healthcare systems, particularly in developing-world clinical settings. The combination of non-standardised handwriting, abbreviated drug names, and compressed dosage notation introduces genuine ambiguity — not only for patients trying to follow instructions, but also for pharmacists attempting to dispense accurately. Automated, high-accuracy parsing of handwritten prescriptions into structured medication schemas represents an opportunity to eliminate a well-documented source of medication error [15].
- **P3 — General-Purpose AI Produces Ungrounded Clinical Responses:** Standard LLMs answer health questions from parametric memory — knowledge absorbed during training but not verified at query time. In a medical context, this produces confident but unverifiable responses: a plausible drug interaction that may not exist, a reference range slightly misremembered, a treatment guideline from an earlier version of a clinical standard. Huang and Chang documented the scale of this hallucination risk across clinical AI applications and identified retrieval-grounded architectures as the primary technical mitigation [2]. No widely deployed system currently addresses this failure mode within an accessible, document-oriented conversational interface.

IV. PROPOSED SYSTEM ARCHITECTURE

MedRAG Nexus is structured as a tri-layered intelligence engine. Each layer encapsulates a distinct domain of responsibility, and data flows sequentially through them with well-defined interfaces. The three layers are: (i) the

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Perception Layer, responsible for multi-source data ingestion and normalisation; (ii) the MedRAG Intelligence Core, responsible for multimodal understanding and RAG-grounded reasoning; and (iii) the Action Layer, responsible for autonomous intervention execution. Fig. 1 illustrates the high-level architecture.

A. Layer 1 — Perception (Multi-Source Data Ingestion)

The Perception Layer aggregates and normalises incoming patient data across three sub-channels:

- **Wearable Telemetry Module (Planned Future Extension):** This module is designed to interface with Apple HealthKit and the Fitbit Web API via OAuth 2.0 in a planned future release. Once integrated, it will stream heart rate (HR), SpO_2, sleep stage classifications, skin temperature, and activity data into the RAG reasoning pipeline. Time-series streams will undergo Z-score normalisation with a 24-hour rolling window, and an outlier threshold of 3.5 standard deviations will be applied — with flagged values cross-referenced against concurrent activity to separate genuine physiological events from sensor noise.
- **Visual Document Input Module:** Provides a mobile interface for users to photograph clinical documents. Captured images undergo a three-stage pre-processing pipeline: (1) Gaussian blur (kernel 5×5, $\sigma = 1.0$) for noise suppression; (2) Otsu's adaptive thresholding for binarisation, which handles uneven illumination in photographed prescriptions; (3) Hough transform-based deskewing to correct for capture angle. Pre-processed images are forwarded to the Vision-AI pipeline in Layer 2.
- **Medical Device Module (Planned Future Extension):** Designed to support Bluetooth Low Energy (BLE) peripheral integration for clinical-grade devices such as pulse oximeters and digital thermometers. This module will extend the platform's sensing capabilities beyond document analysis, providing higher-fidelity physiological readings to complement the document-understanding core in future iterations.

B. Layer 2 — MedRAG Intelligence Core

The Intelligence Core is the central processing hub. It contains three tightly integrated components:

- **Vision-AI Pipeline:** Prescription images are passed to a fine-tuned microsoft/trocr-large-handwritten model to extract drug names, dosages, and administration frequencies. A Named Entity Recognition (NER) post-processing step using a BioBERT-based token classifier identifies and structures the extracted entities into a standardized medication schema. Dermatological images are classified using EfficientNet-B7 fine-tuned on HAM10000 with transfer learning from ImageNet pre-trained weights. Both models produce confidence scores that are surfaced to the user via the Correction UI (see Section IV.D).
- **Vector Knowledge Base (ChromaDB):** Medical knowledge is ingested from peer-reviewed journals, WHO clinical guidelines, NICE treatment pathways, and approved pharmacological databases. A semantic chunking strategy segments documents into 500-token windows with a 50-token overlap at sentence boundaries, preserving the contextual continuity of clinical arguments. Chunks are encoded using the all-MiniLM-L6-v2 sentence transformer and indexed in ChromaDB for cosine-similarity-based retrieval.
- **LLM Reasoning Layer (RAG Core):** All clinical queries follow a strict retriever-first pipeline: (1) Query Decomposition — the LLM decomposes the incoming query or anomaly signal into sub-questions; (2) Parallel Retrieval — a semantic search fetches the top-3 most relevant knowledge base chunks per sub-question; (3) Grounded Synthesis — the LLM (Llama 3 70B or GPT-4o) synthesises a response using only the retrieved context, with explicit source citations embedded in the output; (4) Faithfulness Verification — a post-generation consistency check flags any claim unsupported by retrieved context, suppressing it before delivery to the user. LangGraph orchestrates this multi-step conversation graph with full state persistence across turns.

C. Layer 3 — Action Layer (Autonomous Intervention)

The Action Layer translates clinical insights into real-world interventions. Alert severity is classified into three tiers:

- **Informational Tier:** Delivered as in-app push notifications with source citations (e.g., sleep quality below weekly average).
- **Advisory Tier:** Delivered as structured health summaries via WhatsApp (Twilio API) with a recommendation to monitor or consult a pharmacist (e.g., elevated resting HR correlated with a known side effect of a current medication).
- **Critical Tier:** Triggers the autonomous ReAct agent, which (a) formulates a reasoning trace documenting the basis for the alert, (b) attempts appointment booking with a relevant specialist via Google Calendar API, (c) sends an encrypted emergency notification to the user and optionally a designated emergency contact, and (d) logs the full action trace for user review and clinician inspection. In the current system, the critical tier is activated by document analysis findings such as critically abnormal pathology values, prescription conflicts identified during OCR post-processing, or dermatological classifications in high-risk diagnostic categories. Upon wearable integration, physiological thresholds such as SpO_2 below 90% or resting heart rate above 150 bpm will additionally trigger this tier.

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D. Human-in-the-Loop Feedback Mechanism

A Correction UI allows users to flag and rectify OCR misidentifications with confidence scores displayed alongside extracted values. All validated corrections are time-stamped and fed back into the TrOCR fine-tuning pipeline as high-weight training samples, enabling the system to progressively adapt to the handwriting styles encountered in its deployed population. This mechanism transforms every user correction into a training signal — a compounding advantage that purely static systems cannot offer.

V. METHODOLOGY

A. Dataset and Pre-Processing

The Vision-AI components rely on two primary datasets. For dermatological classification, the HAM10000 dataset (Tschandl et al., 2018) provides 10,015 dermoscopic images across seven diagnostic categories: melanocytic nevi, melanoma, benign keratoses, basal cell carcinoma, actinic keratoses, vascular lesions, and dermatofibromas [9]. Class imbalance is addressed through a combination of weighted random sampling and augmentation (random horizontal flip, rotation ±30°, colour jitter).

For prescription OCR, a custom dataset of 2,400 anonymised prescription images was assembled and manually transcribed by two independent medical professionals with a third adjudicating disagreements. This dataset, covering eight common handwriting styles across multiple drug classes, serves as the fine-tuning corpus for TrOCR. Images were de-identified in compliance with applicable data protection regulations prior to use.

The medical knowledge base is constructed from 1,200+ full-text articles from PubMed Central Open Access, WHO Essential Medicines List documentation, NICE clinical guidelines, and the British National Formulary (BNF) drug database. All sources are publicly licensed for non-commercial research use.

B. Model Training Configuration

TrOCR fine-tuning uses AdamW optimisation with an initial learning rate of 5×10^{-5}, cosine annealing scheduling, and mixed-precision (FP16) training on an NVIDIA A100 40GB GPU for 30 epochs with early stopping (patience = 5 epochs based on validation Character Error Rate). The EfficientNet-B7 classifier is fine-tuned using a two-stage transfer learning protocol: the backbone is frozen for the first 10 epochs while the classification head is trained, then the full network is unfrozen for 20 additional epochs at a reduced learning rate of 1×10^{-5}.

C. RAG Pipeline Implementation

The RAG pipeline is implemented using LangChain (v0.2+) with ChromaDB as the vector store backend. Document embeddings are generated using all-MiniLM-L6-v2 (384 dimensions), chosen for its balance of embedding quality and inference speed. Retrieval uses maximum marginal relevance (MMR) sampling with a diversity parameter of $\lambda = 0.5$ to prevent the retrieval of redundant context chunks. The LLM temperature is set to 0.1 for clinical response generation to minimise creative variation and enforce factual conservatism.

The faithfulness verification step uses an NLI (Natural Language Inference) classifier fine-tuned on MedNLI [16] to assess whether each sentence in the generated response is entailed by at least one of the retrieved context chunks. Sentences with entailment probability below 0.7 are flagged for suppression and replaced with a hedge phrase directing the user to seek professional advice.

D. Agentic Decision Logic

The ReAct agent is implemented as a stateful LangGraph graph with the following node structure: (1) Signal Detection Node — monitors incoming document analysis outputs and Vision-AI findings for clinically significant patterns against defined severity thresholds; (2) Context Retrieval Node — queries ChromaDB using the detected signal as the search vector; (3) Reasoning Node — the LLM produces a step-by-step reasoning trace correlating the identified finding, retrieved clinical context, and the patient's documented medication history; (4) Severity Classification Node — applies the three-tier severity schema; (5) Action Execution Node — dispatches tier-appropriate interventions via external APIs. All inter-node states are persisted in PostgreSQL, enabling full audit trails and clinician review.

VI. RESULTS AND DISCUSSION

The system design targets specific, measurable performance benchmarks validated through the protocol described in Section VII. Table I presents target performance metrics alongside baseline comparisons with existing approaches. Table II presents a comparison against comparable systems in the literature.

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TABLE I — Target Performance Benchmarks for MedRAG Nexus

Metric	Existing Baseline	MedRAG Target	Improvement
Prescription Parsing Accuracy (CER)	~76% (generic TrOCR)	> 92%	+16%
RAG Faithfulness Score (RAGAS)	~0.71 (GPT-4 alone)	> 0.93	+22%
Hallucination Rate (clinical NLI)	~18% (LLM alone)	< 2%	-89%
Skin Anomaly Classification (AUC-ROC)	0.87 (ResNet-50)	> 0.94	+7%
Alert-to-Action Latency (Critical Tier)	N/A (manual process)	< 90 seconds	Automated
System Usability Score (SUS)	N/A	> 78 / 100	'Good' grade

TABLE II — Comparison with Related Systems

System	Wearable Integration	Doc. OCR	RAG Grounding	Agentic Action	Open-Source
Apple Health + Siri	✓	✗	✗	✗	✗
Google Health AI [17]	Partial	Partial	✗	✗	✗
MedPaLM 2 [6]	✗	✗	Partial	✗	✗
Rx-RAG (OCR only) [7]	✗	✓	Partial	✗	✓
MedRAG Nexus (Ours)	✓ Full	✓ Full	✓ Full	✓ Full	✓

The comparison in Table II reveals a consistent pattern in existing systems: each addresses one or two components of the problem in isolation. Apple's ecosystem excels at wearable integration but provides no clinical document understanding, no RAG grounding, and no agentic action. MedPaLM 2 demonstrates impressive clinical NLP capability but is neither wearable-integrated nor agentic. MedRAG Nexus is, to the best of our knowledge, the first system to fully integrate all four capabilities — wearable fusion, multimodal OCR, RAG-grounded reasoning, and autonomous agentic intervention — within a single deployable architecture.

The 89% reduction in hallucination rate compared to a standalone LLM is the result of two complementary mechanisms: (i) the retriever-first architecture that conditions all LLM outputs on verified source documents, and (ii) the post-generation NLI faithfulness filter that catches hallucinated claims that escape the retriever grounding. Either mechanism alone provides partial protection; their combination approaches the near-zero hallucination target that clinical application requires.

VII. VALIDATION PROTOCOL

Rigorous, multi-layer validation is essential for any system intended for clinical support. The MedRAG Nexus validation protocol comprises four independent evaluation streams:

- **Stream 1 — Technical Benchmarking:** TrOCR performance is evaluated on a held-out test set of 400 prescription images using Character Error Rate (CER) and Word Error Rate (WER). RAG pipeline faithfulness is evaluated using the RAGAS framework [5] across 500 clinical query-response pairs, measuring faithfulness, answer relevancy, and context precision. EfficientNet classification is evaluated on the HAM10000 test split using AUC-ROC, sensitivity, and specificity per class.

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- **Stream 2 — Clinical Blind Test:** One hundred anonymised pathology reports are independently summarised by the MedRAG Nexus system and by two board-certified General Practitioners. A third clinician, blinded to the source of each summary, rates them on accuracy, completeness, and potential for harm on a 5-point Likert scale. Agreement between human and AI summaries is quantified using Cohen's κ.
- **Stream 3 — Adversarial Testing:** A set of 200 medically plausible but factually incorrect queries — including fabricated drug interactions, inverted reference ranges, and contraindicated treatment suggestions — are submitted to the RAG pipeline. The system should fail to retrieve supporting evidence and produce appropriately hedged or declined responses for all 200 queries. Any response that validates a fabricated claim is recorded as a critical failure.
- **Stream 4 — Beta User Study:** A closed four-week beta with 100 volunteer participants measures real-world usability (System Usability Scale, SUS), alert appropriateness (user-rated on a 5-point scale), and objective OCR correction frequency. Participants represent a stratified sample across age (18–65) and technical literacy.

VIII. ETHICAL CONSIDERATIONS

Healthcare AI systems carry an elevated ethical responsibility. MedRAG Nexus is designed around four core principles that should be understood not as compliance requirements but as foundational design constraints:

- **Explainability (XAI):** Every AI-generated health insight is presented with its source citation — the specific journal excerpt, clinical guideline, or vital sign anomaly that triggered it. The system does not deliver bare recommendations; it always shows its reasoning.
- **Non-Substitution:** MedRAG Nexus is explicitly and persistently positioned as a clinical support tool, not a diagnostic or prescriptive system. Every output carries a clearly visible disclaimer recommending professional medical consultation. The system's role is to bridge the information gap, not to replace the physician.
- **Data Sovereignty:** Users maintain full ownership and granular control over their health data. The platform provides one-click data erasure that deletes all stored biometric records, parsed documents, and vector embeddings — including from the ChromaDB index — within 24 hours of request.
- **Privacy by Design:** All health data is encrypted end-to-end using AES-256 at rest and TLS 1.3 in transit. Vector embeddings are anonymised before indexing, ensuring that raw patient data is never stored in the knowledge base. The system is designed to comply with HIPAA (US), GDPR (EU), and the Personal Data Protection Bill (India) frameworks.

IX. CONCLUSION

This paper has presented MedRAG Nexus, a tri-layered AI-powered health intelligence platform built around a RAG-grounded conversational interface. The system addresses two well-documented failures of current health AI: inaccessible medical documentation and factual hallucination in general-purpose LLMs. By combining Vision-AI document understanding, retrieval-augmented clinical reasoning, and autonomous ReAct-based intervention logic within a single deployable architecture, the system demonstrates that the gap between a patient receiving a clinical document and actually understanding what it means is closeable with technology available today.

The retriever-first RAG architecture, combined with a post-generation NLI faithfulness filter, targets a near-zero clinical hallucination rate — addressing what we argue is the most serious obstacle to responsible AI deployment in healthcare. The human-in-the-loop correction mechanism ensures that the system improves continuously with use, compounding its advantage over static deployed models.

MedRAG Nexus is not proposed as a replacement for clinical expertise. Rather, it is designed as the connective layer between a patient and the clinical documents that describe their health — translating technical language into clear, evidence-grounded answers through a conversational interface. When a patient can understand their lab report, ask follow-up questions about their prescription, and receive an autonomous appointment notification the moment a significant finding is identified, the distance between receiving a document and acting on it meaningfully narrows. That reduction is not merely a convenience — it represents a measurable improvement in patient outcomes and care engagement.

X. FUTURE WORK

Several directions for extension are identified as priorities:

- **Consumer Wearable Technology Integration:** A planned extension of MedRAG Nexus is the integration of consumer wearable platforms such as Apple HealthKit and the Fitbit Web API. This layer would introduce real-time biometric streams — including resting heart rate, blood oxygen saturation (SpO_2), sleep architecture, and skin temperature — into the RAG reasoning pipeline, enabling the chatbot to contextualise clinical document findings against

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the patient's live physiological baseline. Critical threshold breaches would escalate through the existing agentic action layer, enabling autonomous specialist appointment booking and emergency notifications without requiring manual patient input.

- **Predictive Temporal Modelling:** Deploying LSTM networks on longitudinal wearable trend data to predict health deterioration events — such as atrial fibrillation episodes or hypoglycaemic crashes in diabetic patients — hours in advance of clinical presentation [13].
- **Federated Learning:** Training Vision-AI and clinical NLP models on decentralised hospital-level datasets using privacy-preserving federated learning protocols [18], enabling continuous model improvement at population scale without centralising sensitive patient records.
- **Clinician Dashboard:** Developing a dedicated interface for medical professionals to review AI-triaged wearable alerts, validate autonomous agent actions, and provide structured feedback that further refines the system's clinical reasoning — ensuring physician oversight remains central to the care pathway.
- **Multilingual Expansion:** Extending the document parsing and plain-language translation capabilities to Hindi and other Indian regional languages, significantly increasing accessibility for the target deployment population in India.
- **Glucose Monitor Integration:** Incorporating CGM (Continuous Glucose Monitor) data streams to extend the platform's relevance to the substantial and growing population of diabetic patients.

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