

# MedioQ



cognizant



RAJALAKSHMI  
ENGINEERING  
COLLEGE

## TEAM MEMBERS

### Artificial Intelligence & Machine Learning

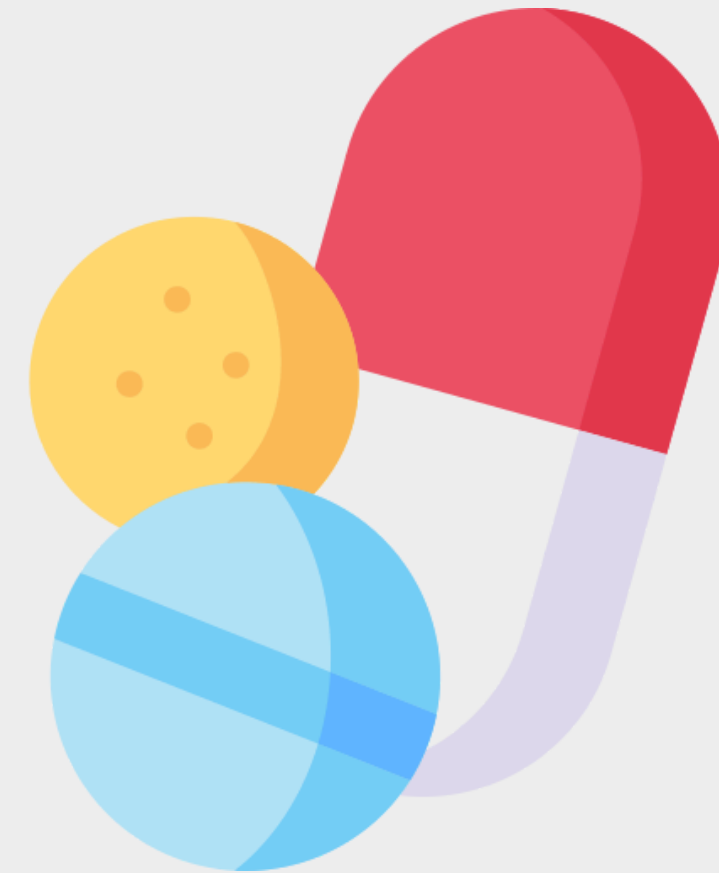
Vishwa M	- 221501179	Viswa V	- 221501180
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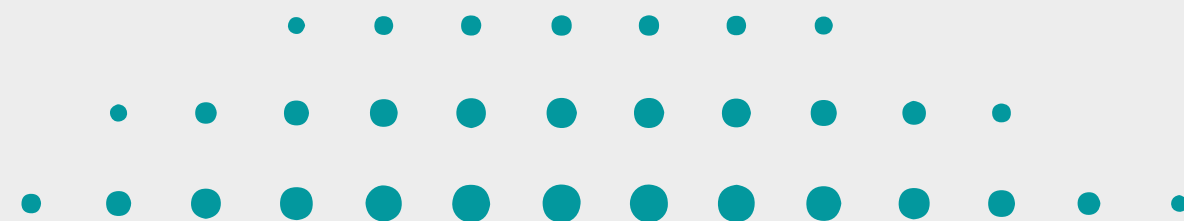


# PROBLEM STATEMENT



**Accessing prescribing information from drug labels is often difficult because:**

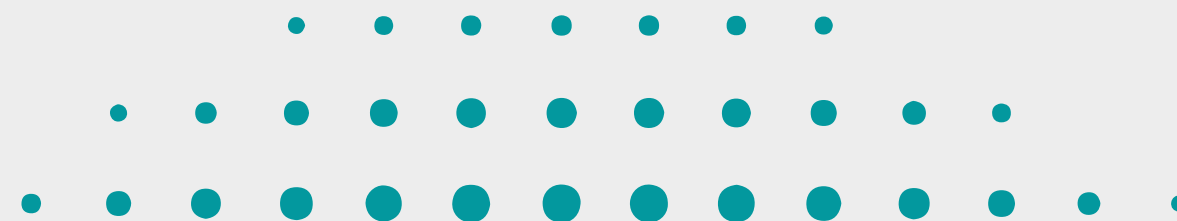
- Drug labels are lengthy and complex.
- Critical details are hard to locate quickly (dosage, interactions, contraindications).
- Unstructured PDF formats make automated extraction challenging.
- Patients and healthcare providers require clear, reliable summaries instead of technical jargon.
- Lack of contextual understanding in existing search tools prevents meaningful follow-up queries.
- Absence of citations reduces trust and traceability of extracted information.



# OBJECTIVES



- To Build a PDF ingestion pipeline to extract drug prescribing details and precautions.
- To Enable intent recognition and vector search for accurate query resolution.
- To Provide reliable answers with citations from source documents.
- To Support patient-specific advice on interactions and administration.
- To Deliver a user-friendly, scalable chatbot with session management.



# EXISTING SYSTEMS

Author(s)/Title	Year	Technique	Description	Outcome
Med-Bot (PDF-Based Medical Assistant with LangChain & ChromaDB)	2025	PyTorch, LangChain, AutoGPT-Q, ChromaDB	PDF-based Q&A on medical literature. Focuses on efficient retrieval and context-aware answers.	Improved accuracy in extracting patient-specific knowledge from medical PDFs.
Community RAG + MedBot GitHub Projects	2025	RAG, FAISS, LangChain, Streamlit	Open-source medical chatbot prototypes for PDF Q&A.	Interactive retrieval-based answers; limited enterprise validation.
MedDoc-Bot (LLM for Pediatric Guideline PDFs)	2024	LLMs (Llama-2, Mistral, Meditron)	Pediatric guideline PDF chatbot; compared different LLMs for reliability.	Found Meditron most effective for healthcare-specific guidelines.
InfoGenie (PDF Information Extraction Chatbot)	2024	HuggingFace embeddings, Chroma, Seq2Seq	Extracts and answers queries from uploaded PDFs.	Provided structured answers; faced scalability challenges.
General-purpose PDF Chatbots (Community Projects)	2023	OpenAI embeddings, Supabase, Pinecone	General chatbot for any PDF Q&A. Popular on GitHub/Reddit.	Easy adoption for non-medical PDFs, lacked domain-specific accuracy.

# **LIMITATIONS OF EXISTING SYSTEM**

S.no	Limitation
1	High resource consumption makes it difficult to scale for low-power environments.
2	Lacks medical domain fine-tuning, leading to unreliable answers for clinical queries.
3	Limited to pediatric hypertension—does not generalize to broader healthcare topics.
4	Struggles to extract accurate answers from tables or charts in medical PDFs.
5	Not optimized for medical data—often misinterprets technical drug-related terms.

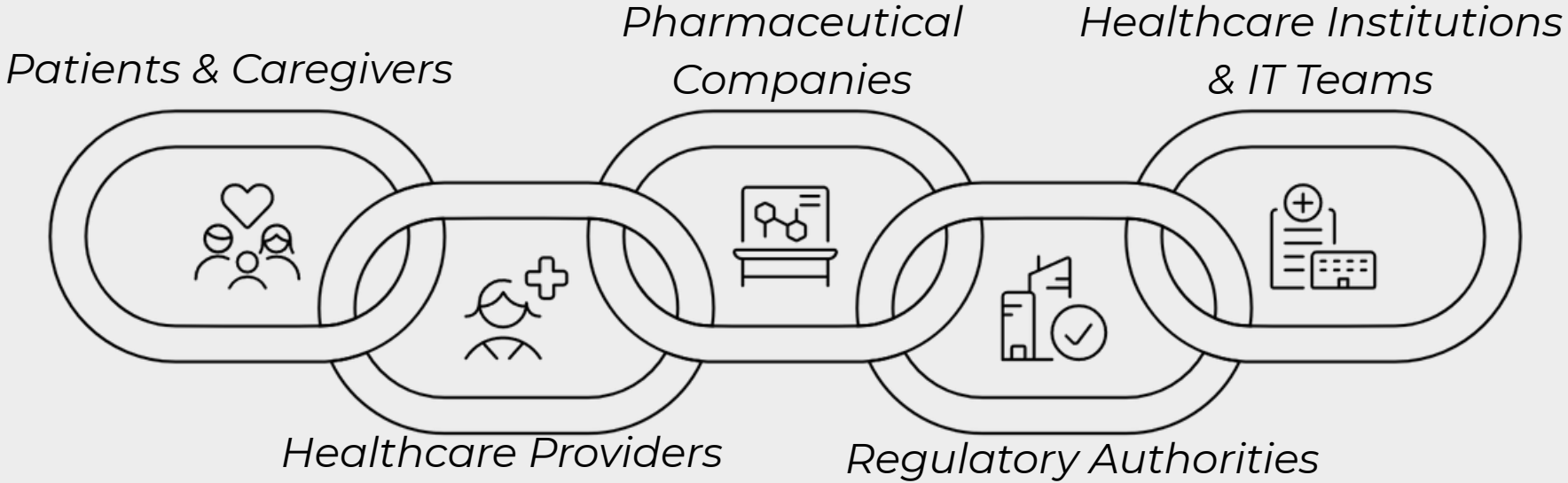
# DOMAIN OVERVIEW

This project operates in the healthcare and pharmaceutical information domain, focusing on drug prescribing information. Patients, caregivers, and healthcare professionals often face difficulties in accessing accurate, structured, and up-to-date drug details from lengthy and complex medical PDFs. The challenge lies in bridging the gap between unstructured prescribing documents and the need for clear, reliable, patient-friendly medical knowledge.

## CHALLENGES :

- Information Overload in lengthy prescribing PDFs
- Unstructured content (tables, figures, OCR text)
- Risk of misinformation or hallucinations from generic chatbots
- Limited personalization (age, gender, medical conditions)
- Heavy dependency on healthcare staff for repetitive queries

## STAKEHOLDERS :

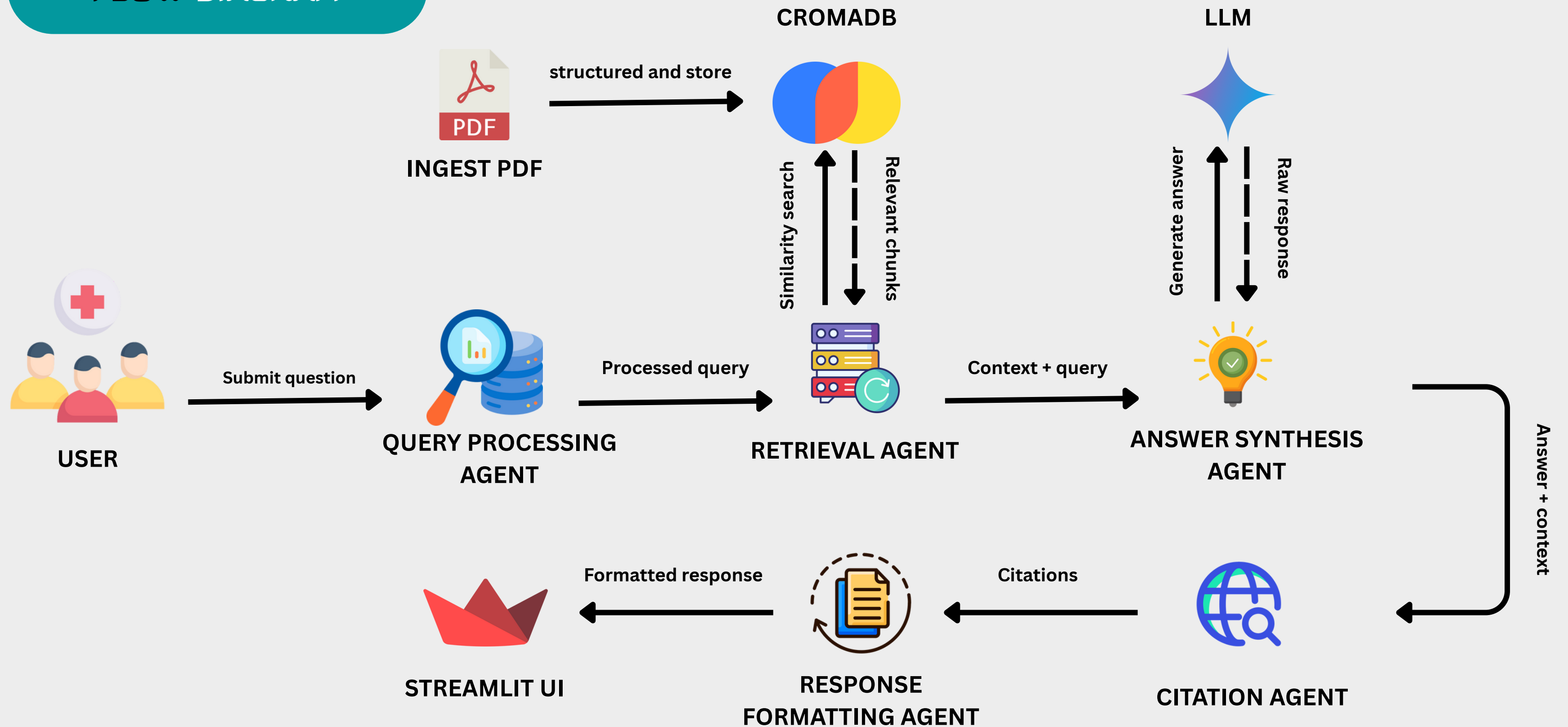


### Impact on Stakeholders

- 1 Improved Accessibility: Simplified and structured access to complex prescribing information enhances decision-making and patient awareness.
- 2 Enhanced Trust & Transparency: Citations with sources build credibility and reduce misinformation risks.
- 3 Personalized Insights: Patient profile-based responses empower users with tailored medical advice.
- 4 Efficiency Gains: Reduces repetitive workload for healthcare staff, enabling them to focus on critical care.
- 5 Regulatory Alignment: Ensures drug information is consistent with approved prescribing labels.

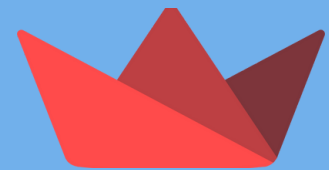


## FLOW DIAGRAM



# TECH STACK

## PROGRAMMING AND FRAMEWORKS



Streamlit



CrewAI

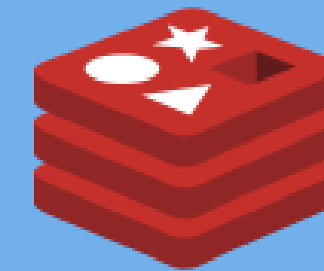


Python

## DATA STORAGE AND RETRIEVAL



SQLite



Redis



ChromaDB

## MACHINE LEARNING AND NLP



Google Gemini API



SentenceTransformers



PyTorch

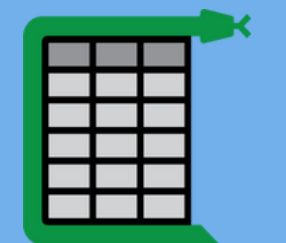
## DOCUMENT PROCESS



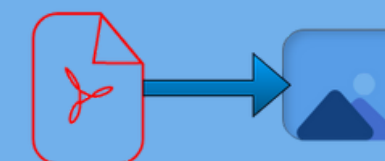
Pytesseract



PyMuPDF



Camelot



pdf2image



Pillow



## USER QUERY

Can Humaria and Rinvoq be used together? Are there any interactions?

## 5 USER INTERFACE

USER NOT SATISFIED WITH RESPONSE

Streamlit

YES

### INTENT AND ENTITY RECOGNITION

USING LLMS  
INTENT : **drug interaction**  
ENTITIES : "Humaria", "Rinvoq"

### VECTOR SEARCH SERVICE

Search the chroma DB to find the top K embeddings

### AGENTIC ORCHESTRATOR

*crewai*

THOUGHT - To answer this, I need to .....  
ACTION :

1. VECTOR SEARCH - "Humaria Interactions"
2. VECTOR SEARCH - "Rinvoq Interactions"

Combine the results

RETRIEVAL

NO

## 2 RETRIEVAL AND QUERY ROUTING AGENT

YES

RELATION EXIST

USER QUERY +  
RETRIEVAL AGENT RESULT

## 3 REASONING AND DOMAIN AGENT

## 4 ORCHESTRATION & ANSWER GENERATION

PROMPT BUILDER  
FINAL PROMPT

FINAL RESPONSE

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### Data Ingestion

Skylizi\_pl.pdf  
Humira.pdf  
Rinvoq\_pl.pdf

Document Parsing  
Identifying Texts  
Identifying Tables  
Parsing Other elements

Structured Representation

Preprocessing  
Text Cleaning  
Normalizing White Spaces  
Removing Headers and Footers

Generating Embeddings  
Data Chunks  
Embeddings

Chunking  
Preprocessed Data  
Data Chunks

Chroma

### VECTOR DATABASE AND INDEXING

Embeddings + Meta Data  
Embeddings + Meta Data  
Embeddings + Meta Data

Meta Data

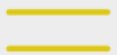



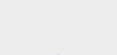
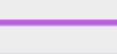
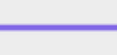
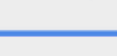
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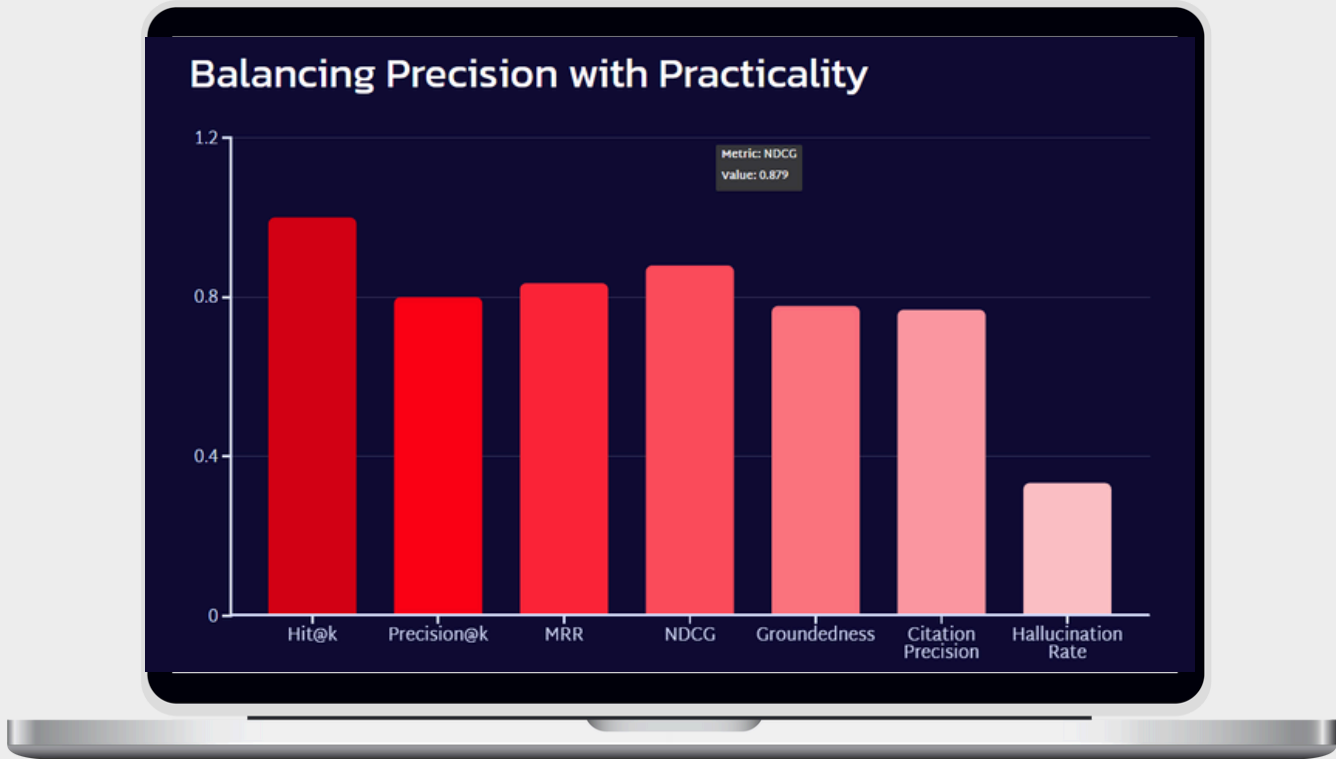
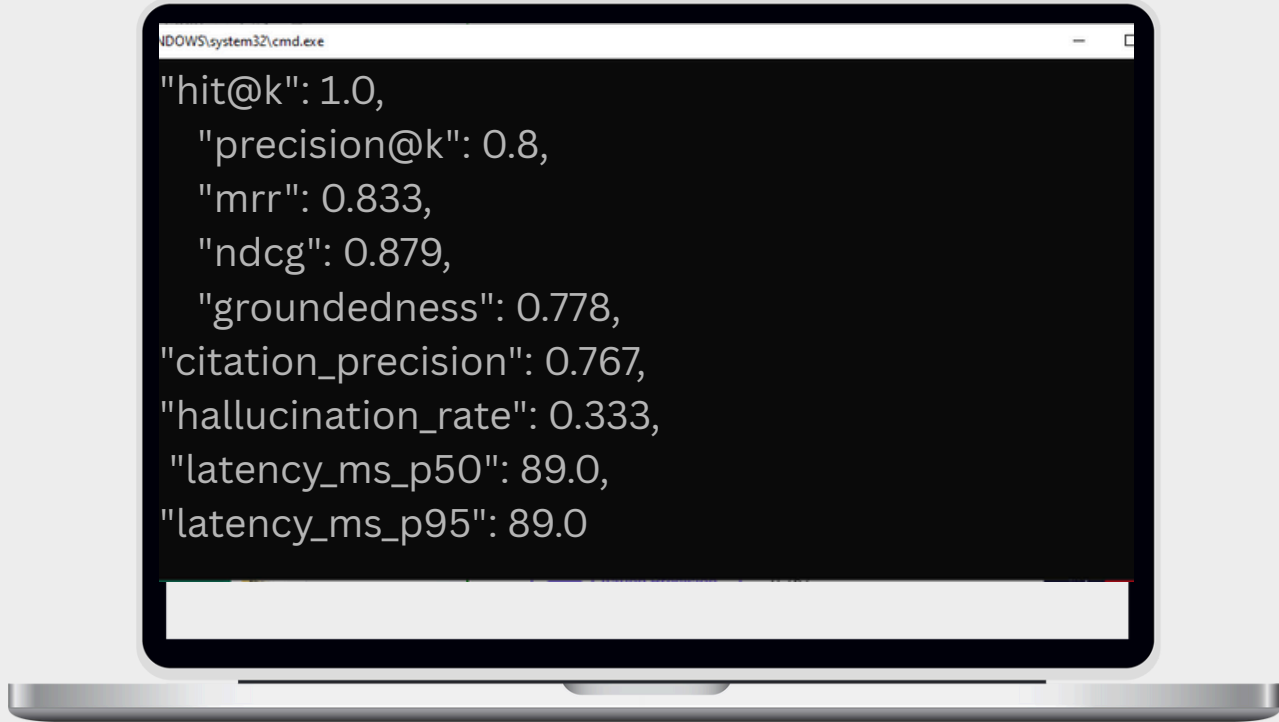
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## 1 DATA INGESTION AGENT


# Evaluation Metrics:

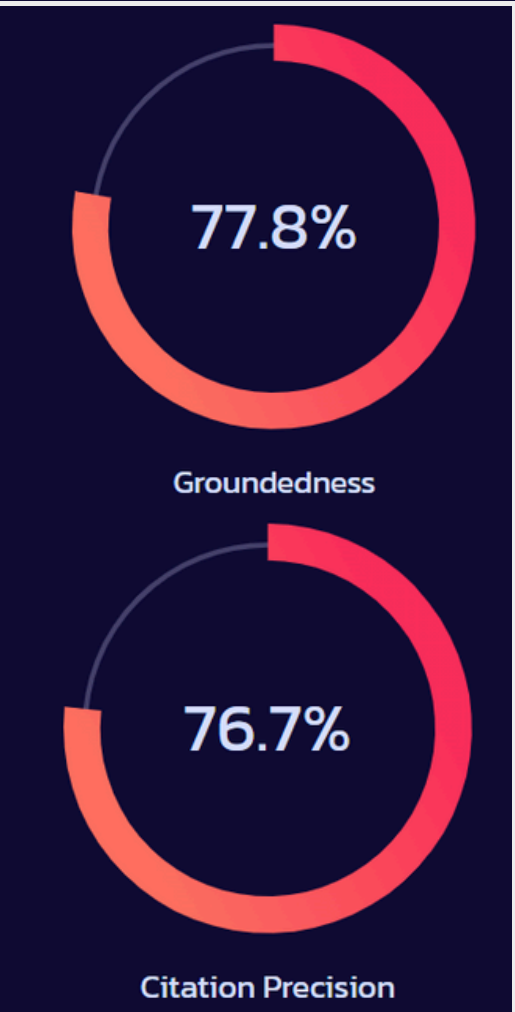
Metric	Value	Description
 <b>Hit@k</b>	1.0	Correct drug always retrieved
 <b>Precision@k</b>	0.80	80% relevant results retrieved
 <b>MRR</b>	0.833	Correct answer ranked near top
 <b>NDCG</b>	0.879	High ranking quality of answers
 <b>Groundedness</b>	0.778	Most answers well-supported by sources
 <b>Citation Precision</b>	0.767	Citations were ~77% accurate
 <b>Hallucination Rate</b>	0.333	~1 in 3 responses unverified
 <b>Latency (p50/p95)</b>	89 ms	Fast responses

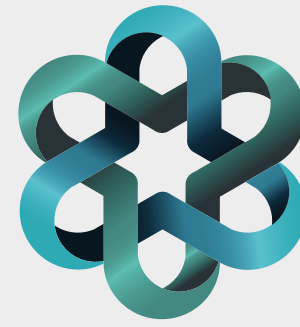


**Accuracy**  
Ensuring correct drug information is delivered.

**Efficiency**  
Providing timely responses to critical queries.

**Trust**  
Building confidence in AI-driven medical tools.





# Thank You

