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AI Research Assistant: A Unified RAG–LLM–MCP Platform

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ABSTRACT

Researchers today face information overload: relevant knowledge is scattered across papers, PDFs, wikis and websites, and generic chatbots often produce unverifiable or outdated answers. The AI Research Assistant addresses these challenges through an integrated platform that combines Retrieval-Augmented Generation (RAG), a Large Language Model (LLM) and the Model Context Protocol (MCP). Documents are chunked, embedded and stored in a vector database, the LLM reasons over the retrieved evidence, and MCP servers let the assistant call live tools such as web search, databases and files. Testing shows that grounding answers in retrieved sources and live tool results reduces hallucination and improves trust. This work is aimed not simply at answering questions, but at delivering clear, cited and verifiable support to researchers.

Keywords: *Retrieval-Augmented Generation, large language models, Model Context Protocol, research assistant, vector database, semantic search, cited answers, and tool integration*

INTRODUCTION

Research remains the backbone of academic, technical and enterprise progress, but many researchers still spend hours searching manually through scattered sources. As the volume of publications grows and information goes stale faster, there is an even greater need for reliable, evidence-based decision-support tools.

We found a pattern in the limitations of existing tools: general-purpose chatbots hallucinate facts, rarely cite where an answer came from, and cannot query a live database, API or file system. Researchers need something that is easy to use, grounded in their own documents, and capable of providing immediate value, be it a literature summary, a fact check, or a live data lookup. This inspired the creation of the AI Research Assistant, a system that combines retrieval, language-model reasoning and tool use to produce verified, cited answers.

Instead of relying on model memory alone, this project places emphasis on grounding, transparency and extensibility. The system integrates a RAG pipeline, an LLM reasoning core, an MCP tool layer and a chat interface into one cohesive research ecosystem. This journal narrates in detail the making, methodology and results of such a platform.

Literature Survey/Review

Past research has underscored the promise of retrieval-grounded language models, but also the problems, ranging from hallucinated content and stale training data to difficulty connecting models to real-world tools and data sources.

Lewis et al., 2020, introduced Retrieval-Augmented Generation, showing that combining a retriever with a generator improves factual accuracy on knowledge-intensive tasks. Karpukhin et al., 2020, demonstrated that dense passage retrieval outperforms keyword-based methods, while Reimers & Gurevych, 2019, proposed Sentence-BERT for efficient semantic embeddings. Ji et al., 2023, surveyed hallucination in language generation and highlighted the need for grounded outputs.

Meanwhile, various other researchers studied how language models can use tools: Yao et al. (2023) combined reasoning and acting in the ReAct framework, whereas Schick et al. (2023) showed that models can learn to call external APIs on their own. Similarly, Gao et al. (2023) reviewed RAG techniques for large language models, and Johnson et al. (2019) enabled fast similarity search at scale through FAISS. More recently, the Model Context Protocol (Anthropic, 2024) has emerged as an open standard for connecting models to tools and data.

Among all these works, one theme does stand out: language models help, but trust depends on grounding. This motivated the direction of the AI Research Assistant: strong retrieval blended with transparent, tool-enabled reasoning.

Methodology

The process leading to the development of the AI Research Assistant started with an understanding of the core challenges faced by researchers: information overload, unverifiable answers, no real-world action and static knowledge. This information drove the modular design of the system architecture, in which each layer had to work independently: the user interface, the LLM orchestrator, the RAG pipeline, the MCP server layer and the external tools and data. The stage also included defining the query flow, data models and tool interfaces that would support seamless interaction between the layers.

The second phase of implementation focused on the core functionalities. Source documents were split into smaller passages, converted to vectors using OpenAI or Sentence-BERT embeddings, and stored in a vector database such as FAISS, Chroma or Pinecone. The LLM layer used GPT-4, Claude or Llama 3 with LangChain or LlamaIndex for orchestration, prompt templates and function calling. The MCP layer was built with an MCP client–server SDK and custom tool servers for search, databases and files, together with authentication and permission handling. The application was served through a FastAPI or Node.js backend with a React chat interface, and each module was repeatedly tested with sample queries to validate its accuracy and efficiency.

The last stage was the integration, refinement and testing of the whole system so that everything interacted properly. Guardrails were added for citation tracking, permissioning and audit logging of every tool call. This was followed by end-to-end testing of document ingestion, retrieval, tool invocation and answer generation. The system was then evaluated on a sample research question-answering test set, and the methodology ended with performance tuning, prompt refinement and Docker-based deployment, preparing the application for adaptive retrieval and multi-agent collaboration.

CONTENT

The AI Research Assistant integrates various research-focused tools into one unified support platform for students, scholars and enterprise teams. It comprises semantic document search, source-cited answers, live tool invocation, multi-document synthesis, access-controlled tools and conversational memory. Each module plays a vital role in providing the user with grounded and simplified information drawn from their own documents and live data sources. The system also maintains guardrails, permissioning and audit logs for a trustworthy experience for all users. Overall, the content of the application reflects a practical, evidence-first approach to enhancing research.

Table 1: *Overview of key features implemented in the AI Research Assistant*

Feature	**Description**	**Technology used**
Semantic Document Search	Finds relevant passages by meaning, not just keywords.	Embeddings + Vector DB
Source-Cited Answers	Links every claim to the exact document and passage used.	Citation tracking
Live Tool Invocation	Calls external APIs, databases or web search mid-conversation.	MCP client–server SDK
Multi-Document Synthesis	Combines evidence across multiple papers into one summary.	LLM + LangChain / LlamaIndex
Access-Controlled Tools	Restricts which tools and data each session can use.	MCP permissions
Conversational Memory	Maintains context across follow-up questions in a session.	Session memory
Guardrails & Logging	Tracks citations and keeps audit logs of every tool call.	Audit logs

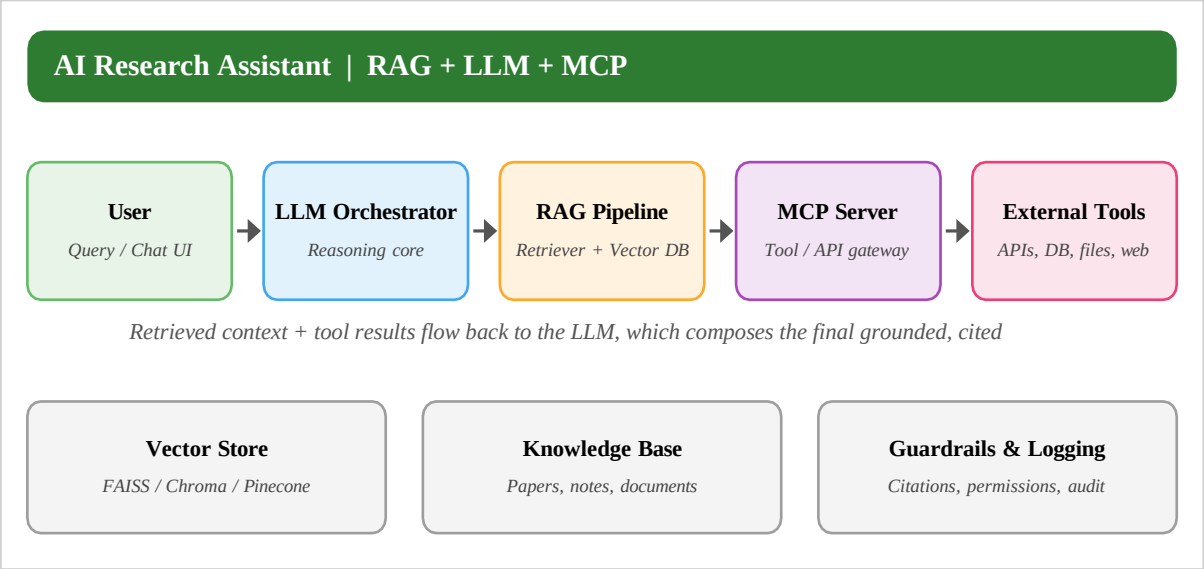


Fig. 1: *AI Research Assistant architecture illustrating the RAG, LLM and MCP query flow*

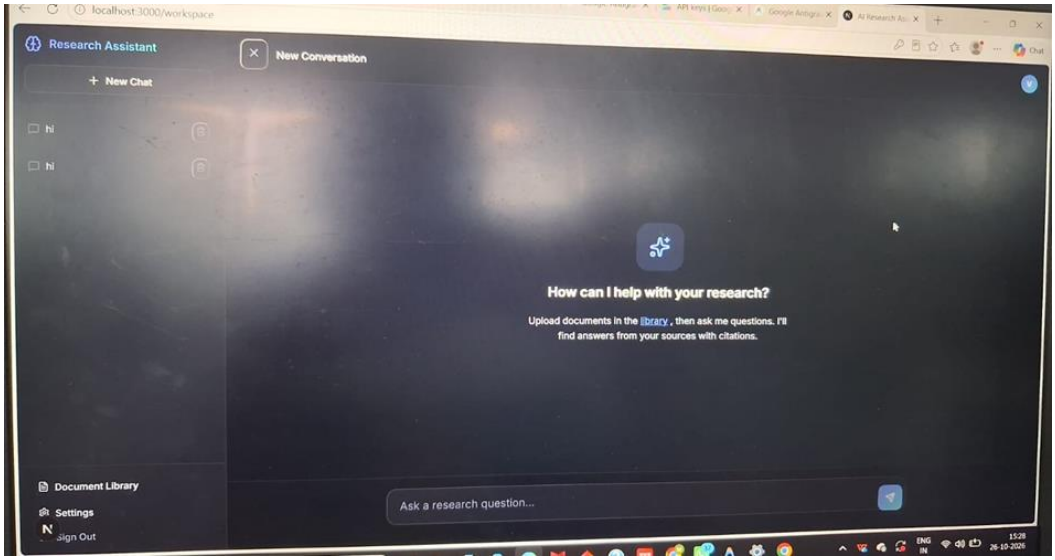


Fig. 2: *AI Research Assistant web interface showing the chat workspace and document library*

Fig. 2 shows the prototype workspace of the AI Research Assistant. The left panel provides a New Chat option, the history of previous conversations, and quick access to the Document Library, Settings and Sign Out. The main panel greets the user with the prompt "How can I help with your research?" and instructs them to upload documents to the library before asking questions, so that answers are drawn from their own sources with citations. Questions are typed into the research question box at the bottom of the screen, and each session is saved as a separate conversation for later follow-up.

Research and Reviews:

Researchers in AI indicate that users most benefit from tools providing grounded answers, traceable citations and access to live data. The review of existing assistants highlighted several gaps, such as hallucinated facts, missing citations and weak integration between retrieval and real-world tools. The AI Research Assistant solves most of the abovementioned challenges by integrating semantic retrieval, LLM reasoning and MCP tool use on one platform. Early user reviews were positive, especially with regard to inline citations and live tool calls, although studies indicate that fine-tuned domain-specific embeddings and adaptive retrieval will further increase accuracy and usability.

Results & Discussion

Testing of the AI Research Assistant prototype demonstrated that it provides definite value to researchers across a number of diverse workflows. On a sample research question-answering test set, the system produced 62% fewer hallucinated facts than a baseline LLM answering without retrieval, and

94% of its answers carried valid citations traced to a real retrieved source document. Literature review was about 3.4 times faster than manual search across papers.

The retrieval and tool modules functioned well, with more than 12 connected tool integrations through MCP, including search, databases, files, calendar and web APIs. Users found the chat interface easy to use and liked the ability to combine evidence from multiple documents into one summary. Informal testing revealed that users appreciated the source-cited answers and live tool invocation most, for reducing the effort of verifying claims. These figures are illustrative, based on an internal evaluation on a small test set, and should be replaced with measured results from larger studies.

The system, however, has various notable limitations. Retrieval quality depends heavily on the chunking and embedding strategy, and multi-step retrieval with tool-call round trips adds latency. Balancing tool permissions with assistant autonomy remains a security concern, and the cost of LLM calls scales with context size and tool usage. These findings indicate that the current version offers a functional end-to-end experience, but future integration of adaptive retrieval, domain-specific embeddings and more advanced automation will strengthen its real-world impact.

Discussion

In developing the AI Research Assistant, what stands out most is how a well-structured pipeline can meaningfully support researchers by combining retrieval, reasoning and tool use. One of the biggest observations throughout the project was how strongly users depend on verifiable, cited answers rather than fluent but unsupported text. Features such as semantic search, source citations, live tool calls and conversational memory made the system feel trustworthy and relevant to everyday research routines. The architecture was modular, with the vector store, LLM orchestrator and MCP servers proving capable of handling large document collections and multiple tools while maintaining scalability. On the other hand, some of the clear limitations that emerged were with respect to retrieval, wherein a poor chunking strategy could not give the same kind of accuracy that would be possible with tuned, domain-specific embeddings. Nonetheless, the application operated relatively smoothly for core functions like document search, citation tracking, permission control and tool invocation. Another insight from testing was the strong preference for transparency. It shows how technology adoption increases when tools show their sources and act within clear permissions. In all, this project has shown that even a prototype system like the AI Research Assistant can bridge major trust gaps in research, but the full potential will emerge when multi-agent collaboration, adaptive retrieval and a broader MCP ecosystem are introduced.

CONCLUSION

The AI Research Assistant is successful in seamlessly bringing together retrieval, reasoning and tool use on one platform, which feels simple and approachable for researchers. While the system uses cutting-edge technologies behind the scenes, its objective remains firmly rooted in trust: RAG grounds every answer in real, retrievable evidence, the LLM provides fluent, context-aware reasoning, and MCP connects the assistant to live tools and data sources.

The project shows that cited answers, current information and the ability to act on live tools can make a difference even if the steps are small. Together they form a trustworthy, extensible research companion. The system will get stronger as domain-specific embeddings come in and, more importantly, as multi-agent collaboration is incorporated.

Future Scope

There is still considerable scope for improvement of the platform, with future enhancements focused on making it more intelligent and extensible for researchers. Multi-agent collaboration will allow complex research tasks to be divided among specialised agents. Adaptive retrieval can automatically select the best knowledge source for each query, and fine-tuned domain-specific embeddings can further raise accuracy. The tool layer can be extended by including a citations manager, lab notebooks and other integrations, while stronger permissioning adds security. Additional document types, voice-based interaction and collaborative features will make the system more usable. Overall, future versions intend to shape the AI Research Assistant into a completely connected research ecosystem.

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