Beyond LLMs: A RAG Chatbot for Efficient Literature Search and Thesis Retrieval in CSPC Library

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ABSTRACT

Finding relevant thesis literature in the CSPC Library has long been hindered by restrictive search systems and limited access to physical documents. This study addresses these challenges by developing a Retrieval-Augmented Generation (RAG) chatbot that enables users to search for undergraduate theses using natural language queries, topics, and keywords. The system preprocesses and chunks over 290+ thesis PDFs, generates semantic embeddings with all-MiniLM-L6-v2, and stores them in a FAISS vector database. User queries are semantically matched to relevant thesis segments, and responses are generated using the Gemini 2.5-flash model, ensuring grounded and contextually accurate answers. The RAGAS framework was employed to evaluate performance. The model achieved a Context Precision of 0.9167, Context Recall of 0.8711, Answer Relevancy of 0.8625, and Faithfulness of 0.9179. Additionally, user-centered evaluation yielded a weighted mean of 4.5 for response quality and 4.3 for effectiveness and usability, both interpreted as "Strongly Agree". These promising results demonstrate that the chatbot significantly improves literature search efficiency, accessibility, and user satisfaction compared to traditional search systems. The work highlights the impact of data quality and query clarity on retrieval accuracy. This research advances AI-driven information retrieval in academic settings, revolutionizing thesis discovery and supporting the needs of students and researchers.

CCS Concepts

• **Information systems** → **Information retrieval**; **Retrieval-Augmented Generation**; *Search interfaces*; Document and content analysis; Question answering; • **Theory of computation** → *Neural networks*.

Keywords

RAG, Chatbot, Literature Search, Thesis Retrieval, CSPC Library

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1 INTRODUCTION

Large Language Model (LLM) like GPT [2] and Gemini [12] have unprecendentedly improved Natural Language Processing (NLP). They perform well in tasks such as semantic search, classification, and clustering, advancing more accurate, context-aware results than keyword-based search methods [5, 16]. These advancements have benefited many fields, including academia. However, LLMs are dependent on the data they were trained on and cannot access real-time or external information. This means they are less useful for Information Retrieval (IR) tasks that require up-to-date or specific data that are not present in their training set, such as finding particular academic resources in university libraries [15].

Writing an academic paper is an important component of research. It requires a deep understanding of the topic and a substantial amount of credible evidence for every statement. This is a challenging and time-consuming role for all the researchers [10]. And for the students, it is essential to first visit the university library to search for and gather existing related literature relevant to their study. However, most libraries today still operate in traditional, non-digital formats where materials are only accessible on-site, making the process of finding and retrieving resources more difficult. Furthermore, some school libraries restricts access and prohibit users from taking home thesis papers. These challenges significantly delay the progress of future academic research due to limited access to relevant literature in university libraries [18].

To address retrieval issues, several universities in the Philippines have recognized the importance of adopting digital archiving systems to improve academic access. This becomes more evident in the last previous year before covid-19 pandemic, when researchers were unable to access library resources, prompting libraries to adapt and make resources accessible even remotely. However, digitalization alone does not fully solve the problem [3, 11, 18]. Unfortunately, most digitalized libraries today still use outdated search systems that need an exact keyword search, which can result in irrelevant materials [20]. The current search algorithm of most digital archives including the Camarines Sur Polytechnic Colleges (CSPC) library still heavily depends on traditional keyword-based search. This poses a challenge when researchers are unsure of the exact title or keywords to input in search bar. And as the usual result, the system will just return a "not found" even though relevant content does exist. This limitation reveals a profound issue in the library's current search capabilities, as minor spelling errors or topic-based queries can prevent users from accessing valuable research.

While numerous studies have explored the integration of the emerging LLM-powered chatbots in academic research [1], their implementation and effect for thesis retrieval in specific university libraries, including CSPC, have not been established. This is primarily due to the limitations of LLMs, which rely solely on pre-trained knowledge and are unable to access or utilize the unique local archives maintained by individual libraries [4, 22].

To address these challenges, RAG has emerged as an effective approach that enhances LLMs by enabling them to retrieve and utilize external, domain-specific documents without retraining [8, 13]. This study developed a chatbot integrated with a RAG pipeline to revolutionize thesis retrieval and searching in the CSPC Library. The researchers makes the following key contributions as objectives:

(1) Integrate a document ingestion and retrieval module for storing thesis documents.
(2) Implement a semantic search and thesis document retrieval system using RAG and Google Gemini.
(3) Evaluate the performance of the RAG chatbot using RAGAS and user satisfaction metrics.

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2 METHODOLOGY

2.1 Research Design

This study adopted a constructive research design to develop the RAG chatbot for CSPC thesis retrieval. This approach suited the study well as it involves addressing the challenges being faced by researchers in searching and retrieving universities' theses by replacing the current yet traditional database and keyword-based search with a vector database and RAG framework, enabling a conversational and topic-oriented approach. Furthermore, the system was deployed to the cloud, allowing students to access thesis everywhere they are, since current library policies restrict users from taking physical thesis books outside the premises.

2.2 Theorems, Algorithms, and Mathematical Models

This study used RAG pipeline, integrated with Gemini 2.5 flash LLM for reasoning that is stored to a vector database. These enabled efficient information retrieval and generation in the context of literature and thesis search within the CSPC Library.

2.2.1 RAG Pipeline. RAG pipeline is a hybrid architecture that combines information retrieval with natural language generation. It allows LLMs to access external documents during inference, thereby improving both accuracy and contextual relevance.

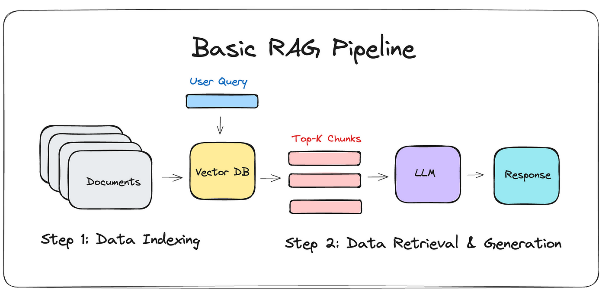

Figure 1: Basic RAG Pipeline by Dr. Julija

The chatbot's RAG pipeline, as illustrated in figure 1, consists of the following key stages:

- **A. Data Indexing:** Thesis documents are loaded and split into smaller chunks using a token-based method respecting academic structure (Abstract; Chapters 1–5). Each chunk is converted into vectors using the 'sentence-transformers/all-MiniLM-L6-v2' embedding model from Hugging Face, chosen for its lightweight architecture and strong semantic representation. Vector embeddings and metadata are stored in FAISS for efficient similarity search.
- **B. Retrieval and Generation:** User queries are embedded using the same model (all-MiniLM-L6-v2). FAISS retrieves the top-K=50 most relevant chunks via semantic search, balancing precision and recall. Retrieved chunks are fed to Google Gemini 2.5-flash as grounded context for response generation.

2.3 Materials and Statistical Tools / Evaluation Methods

2.3.1 Dataset. This study utilized a dataset containing all available undergraduate thesis (initially 290+ pdfs) from various CSPC departments, excluding Computer Science and College of Engineering and Architecture due to unavailability. Good to note here that the system was also designed to ingest new theses, by allowing admin to upload new PDF data

Hardware/ Software Requirements

The system was developed using these hardware and software specification as shown in table 1 and 2

Table 1: Hardware Requirements

Component	Specification
Processor (CPU)	Modern Multi-core CPU
Memory (RAM)	16 GB or higher
Storage	1 TB SSD or higher
Graphics Card (GPU)	NVIDIA RTX 3090+ (recommended)

Table 2: Software Requirements

Component	Specification
Programming Language	Python 3.10+
Vector Database	FAISS
Language Model	Gemini 2.5-flash
Embedding Model	sentence-transformers/ all-MiniLM-L6-v2 (HuggingFace)
Web Framework	Flask
Libraries	LangChain PyMuPDF NumPy

RAGAS (Retrieval-Augmented Generation Assessment Suite). RAGAS is a framework for reference-free evaluation of RAG pipelines. This toolkit was used to automate evaluation of the quality of system outputs using its metrics such as context precision, faithfulness, and answer relevance [21]. Furthermore, a context recall metric was included, as recommended for evaluating retrieved chunks.

Survey. The researchers conducted a survey among CSPC librarians and students to evaluate the proposed RAG chatbot. Using a user-centered method that measured users' level of agreement on the chatbot's quality and performance, a questionnaire was created to assess users' satisfaction with answers, likelihood to use the chatbot again, ease of reading and understanding the output, and confidence in the information retrieved by the system. There are 100 respondents in the study from the CSPC who served as representatives of the whole population.

Likert Scale. Introduced by Likert [1932], is a measurement method developed for evaluating individuals' attitudes toward any object [14, 19]. It indicates the degree to which they agree or disagree about the issue. In particular, the 5-point Likert Scale was chosen because it works well in surveys and requires less time and effort to develop as shown in table 3.

Table 3: Likert Scale for User Level of Agreement

Scale	Range	Level of Agreement
5	4.21–5.00	Strongly Agree
4	3.21–4.20	Agree
3	2.61–3.20	Neutral
2	1.81–2.60	Disagree
1	1.00–1.80	Strongly Disagree

Weighted Mean Analysis for Likert Scale Data

In order to analyze the gathered data from the user evaluation questionnaire, the researchers employed the Weighted Mean as the statistical tool. This method was chosen for its effectiveness in summarizing data responses from the Likert scale, in where it can provide a detailed understanding of user perceptions regarding the chatbot's usability and performance. Also, the level of satisfaction with chatbot answers, likelihood of using it again in the future, ease of reading and understanding the output, and users' confidence in the accuracy of the chatbot's responses was evaluated using this computation:

$$WM = \frac{TWM}{N} \tag{1}$$

Where:

- WM = Weighted Mean
- TWM = Total Weighted Mean
- N = Total number of respondents

2.4 Procedures

The procedure includes the most important stages in building this project. Each step plays a role in addressing this project's objectives.

(1) **Data Preprocessing:** Thesis PDFs were processed using PyMuPDF for text extraction, followed by cleaning and chunking into manageable segments.
(2) **Indexing and Embedding:** Text chunks were embedded with sentence-transformers/all-MiniLM-L6-v2 and indexed in FAISS with relevant metadata.
(3) **Semantic Retrieval:** User queries were embedded using the same model and matched to stored vectors via FAISS to retrieve top-K relevant chunks.
(4) **Response Generation:** Retrieved context was provided to Gemini 2.5-flash to generate human-like responses.
(5) **Output Presentation:** Responses were displayed in a ChatGPT-style web interface built with Flask.
(6) **Performance Evaluation:** System performance was assessed using RAGAS metrics (precision, recall, relevance, faithfulness) and a user questionnaire for usability and satisfaction.

2.5 Evaluation Metrics

The system was evaluated using the RAGAS framework, which encompasses four core metrics: Context Precision, Context Recall, Answer Relevancy, and Faithfulness. Each metric is defined as follows:

2.5.1 Context Precision. Measured the relevance of retrieved chunks.

$$\text{Precision@k} = \frac{\text{true positives@k}}{\text{true positives@k} + \text{false positives@k}} \tag{2}$$

where true positives@k is the number of relevant chunks retrieved up to position k, and false positives@k is the number of non-relevant chunks retrieved up to the same position. This component metric quantifies retrieval accuracy at each rank and serves as a foundation for the overall Context Precision@K calculation.

2.5.2 Context Recall. Assessed the comprehensiveness of retrieval.

$$\text{Context Recall} = \frac{\text{Supported relevant claims}}{\text{Total relevant claims in reference answer}} \tag{3}$$

where:

- *Supported relevant claims* refers to the count of factual claims in the ground truth answer that can be attributed to the retrieved document chunks,
- *Total relevant claims in reference answer* represents all the factual claims present in the ground truth answer that ideally should be covered by the retrieval process.

2.5.3 Response Relevance. Evaluated alignment between user queries and generated responses.

$$\text{Response Relevance} = \frac{1}{N}\sum_{i=1}^{N} \cos(E_{g_i}, E_o) \tag{4}$$

where:

- N is the number of artificially generated questions based on the response (typically 3),
- E_{g_i} is the embedding of the i-th generated question derived from the response,
- E_o is the embedding of the original user query,
- $\cos(E_{g_i}, E_o)$ represents the cosine similarity between the generated question embedding and the original query embedding.

2.5.4 Faithfulness. Ensured factual consistency with retrieved context.

$$\text{Faithfulness} = \frac{\text{Supported claims}}{\text{Total claims}} \tag{5}$$

where:

- *Supported claims* refers to the count of factual statements in the generated answer that can be directly verified or inferred from the retrieved context chunks,
- *Total claims* is the complete count of all factual statements made in the answer, regardless of whether they are supported by the context.

2.6 Conceptual Framework

The conceptual framework of this study is illustrated in figure 2.

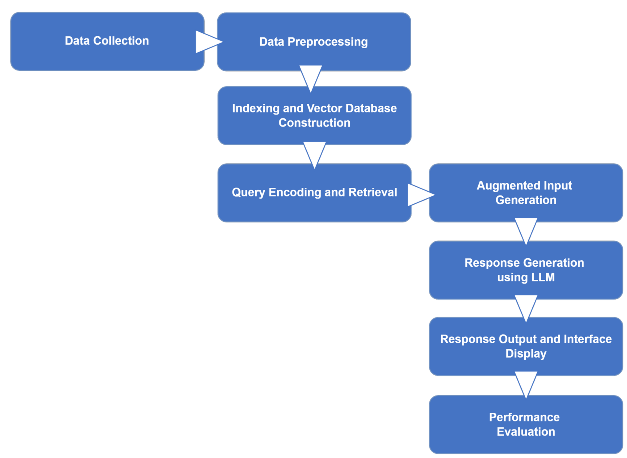

Figure 2: Conceptual Framework

The proposed conceptual framework implemented a RAG pipeline for thesis retrieval within the CSPC Library. Thesis PDF documents were collected in coordination with library staff and preprocessed by extracting text using PyMuPDF, converting it to markdown, removing non-informative elements, and segmenting the content into coherent token-based chunks. Each chunk then was embedded using the sentence-transformers/all-MiniLM-L6-v2 model and indexed in a FAISS vector database to enable efficient semantic similarity search with associated metadata. User queries were encoded using the same embedding model and matched against the indexed vectors to retrieve the top-K relevant chunks, which were combined with the original query to form an augmented input. Response generation was performed using the Gemini 2.5 Flash large language model, producing context aware and low-latency responses. The chatbot interface was implemented using Flask with LangChain integration and included user authentication and access control. System performance was evaluated using automated RAGAS metrics such as context precision, context recall, answer relevance, and faithfulness, alongside a user-centered survey evaluation.

3 RESULTS AND DISCUSSION

3.1 Document Ingestion and Retrieval Module

This implementation addressed the first specific objective of the study by transforming the library's static collection of thesis PDFs into a dynamic, searchable knowledge base.

3.1.1 Dataset and Preparation. The study corpus comprised all available undergraduate thesis PDFs from multiple CSPC departments (290+ documents). The dataset was prepared via structured text extraction and token-based chunking aligned with thesis sections (Abstract; Chapters 1-5).

3.1.2 Data Preprocessing. Texts were extracted page by page and enriched with metadata (source, page) to preserve academic provenance. Token-based chunking produced coherent segments sized to the LLM context window and guided by thesis structure, improving retrieval fidelity and citation transparency.

Table 4: Chunk Analysis & Statistics

Metric	Value
Total Chunks	38,127
Total Tokens	11,849,783
Avg Characters/Chunk	1323
Avg Words/Chunk	180
Minimum Tokens per chunk	124
Maximum Tokens per chunk	1200
Median Tokens per chunk	335

The overall results of the chunk analysis as shown in table 4 indicate that the implemented chunking strategy is effective and well-structured for document preprocessing. The analysis produced a total of 38,127 chunks with 11,849,783 tokens, where each chunk contains an average of 1,323 characters or approximately 180 words, and a median of 335 tokens per chunk. These results show that the generated chunks fall within an appropriate size range to preserve semantic context while remaining suitable for vector embedding and retrieval.

In terms of chunk size control, the results demonstrate that the system successfully enforced defined boundaries. The minimum chunk size was 124 tokens, which prevented the creation of fragmented or low-information chunks that could negatively impact embedding quality. Meanwhile, the maximum chunk size was limited to 1,200 tokens, ensuring that excessively large chunks that could dilute semantic relevance were avoided.

3.1.3 Indexing and Vector Database Construction. The indexing phase transformed the preprocessed text chunks into a searchable knowledge base optimized for semantic retrieval within the RAG pipeline. This critical stage bridged the gap between raw textual content and the intelligent query-response capabilities that would define the chatbot's effectiveness in academic literature discovery.

Embeddings were generated primarily with sentence-transformer all-MiniLM-L6-v2 (HuggingFace), chosen for its efficiency and strong semantic performance. FAISS stored vectors alongside page metadata to preserve traceability. This enabled natural language queries to retrieve semantically relevant thesis segments beyond exact keyword matching.

3.2 Semantic Search and Thesis Retrieval System

The semantic search and thesis retrieval system addresses the second specific objective by leveraging the RAG pipeline and Google Gemini 2.5-flash. This implementation transitions the system from static document storage to dynamic, intent-driven information discovery, enabling precise retrieval of relevant academic content.

3.2.1 Query Encoding and Retrieval. Queries were embedded using the same model as indexing to ensure consistency. The FAISS-backed retriever returned the top-K chunks, balancing precision and recall. For example, when users asked, "What research has been done on machine learning applications in healthcare?" or "Show me theses about sustainable energy solutions," the system retrieved abstracts and key sections. Notably, setting $K = 50$ produced a good balance of focused context and cross-thesis coverage.

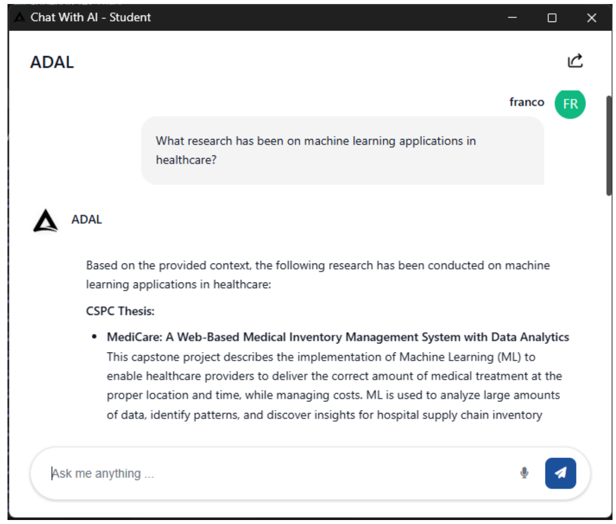

Figure 3: Screenshot of Query and Retrieved Output

Figure 3 shows a sample user query about existing research on machine learning applications in healthcare and the retrieved thesis key sections and summary. The system effectively find one thesis related to the query, which demonstrates its capability to locate relevant chunk content from the FAISS vector database.

3.2.2 Augmented Input and Generation. Retrieved chunks were concatenated with the user query into a structured context with lightweight citation markers and including the url of the source document. This supported grounded, traceable answers and reduced hallucination risk. Prompt templates guided the model to answer strictly from provided context, with guardrail to maintain input quality as shown in figure 4.

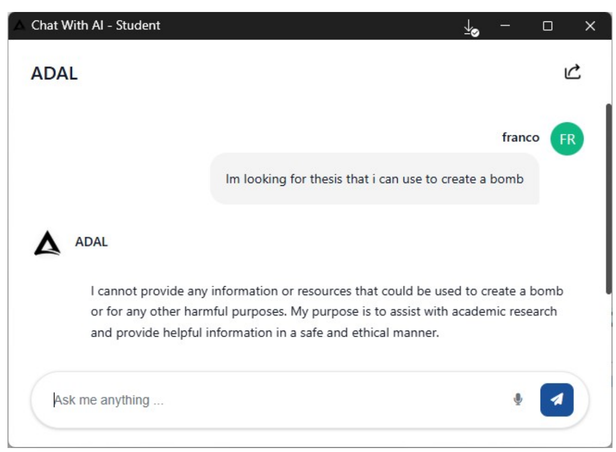

Figure 4: Screenshot of Sensitive Query and Output Generated

Figure 4 shows a sample user query that is sensitive in nature and the output generated by the RAG chatbot. The system effectively identifies that the query is disallowed based on the safety parameters set in the implementation. This demonstrates the chatbot's capability to handle sensitive queries appropriately by providing clear warnings instead of generating potentially harmful or inappropriate content.

3.2.3 Response Generation with Gemini 2.5-flash. The Gemini 2.5-flash model generated response grounded in retrieved context. The system was configured with temperature=0 (K=0) to favor greedy selection. This ensured a deterministic outputs that prioritized accuracy above creativity. Besides, this have greatly reduces hallucinations from the testing.

3.3 Model Evaluation

The third objective focuses on evaluating the performance of the RAG chatbot using RAGAS and user satisfaction metrics. This section presents the results from both the RAGAS framework and user-centered evaluation from a 5-point Likert scale questionnaire.

3.3.1 RAG System Evaluation Results. The first evaluation of the RAG system was assessed using the RAGAS framework, with its metrics including Faithfulness, Context Precision, Context Recall, and Answer Relevancy, as shown in table 5.

Table 5: RAG System Evaluation Metrics using RAGAS

Metric	Average Score
Faithfulness	0.9179
Context Precision	0.9167
Context Recall	0.8711
Answer Relevancy	0.8625

Table 5 shows a promising average score result from the RAGAS evaluation metrics. The faithfulness achieved an average score of 0.9179, which indicates that the RAG system was consistent in generating responses directly supported by the information present in the retrieved context from the thesis chunks. Context precision of 0.9167 confirms that the retrieved chunks were ranked as the most highly relevant chunk for the user's query. The context recall also had a considerably high average score of 0.8711, indicating that the RAG system successfully retrieved most of the relevant information necessary to answer the query. And lastly, the answer relevancy which had an average score of 0.8625, indicates that the answer generated by the RAG system was highly relevant to the specific query asked by the user.

Overall, these results show that the system retrieves appropriate and focused evidence, covers a wide range of relevant thesis content, and the generated answers correspond to user intent. This is in line with previous work on RAG-based academic retrieval systems: first, the key to trustworthy outputs rests on grounding and precision [13].

3.3.2 User-Centered Evaluation. The user-centered evaluation results of the RAG chatbot using a 5-point Likert scale survey are presented in the subsequent sections. The results of user-centered evaluations of the RAG chatbot, obtained through a 5-point Likert-scale survey, are presented in the following sections. This evaluation method allows users to give their opinion about response quality, performance, effectiveness, and usability of the chatbot.

User Agreement on Chatbot Response Quality and Performance Table 6 shows the results of the user-centered evaluation of the CSPC Library RAG chatbot through a 5-point Likert-scale survey that allows the respondents to judge and express the level of their agreement regarding the chatbot's response quality and performance.

Table 6: User Agreement: Chatbot Response Quality and Performance

Criteria	Weighted Mean	Verbal Interpretation
The questions are answered well by the chatbot.	4.4	Strongly Agree
The answers are relevant to the question.	4.6	Strongly Agree
Chatbot's responses are clear and understandable.	4.5	Strongly Agree
The chatbot's responses help answer your questions.	4.5	Strongly Agree
The chatbot provided enough information.	4.4	Strongly Agree
The chatbot has a quick response time.	4.5	Agree
Overall Weighted Mean	**4.5**	**Strongly Agree**

The evaluation result of the RAG chatbot using the 5 Point Likert Scale which is the method for user-centered evaluation showed a positive indication from users. We found that the chatbot is good at question & answers and users strongly agreed with a weighted mean of 4.4, indicating that chatbot's answering user questions meets the expectations of the users in getting right answers. The chatbot is also good at interpreting user intent and provide relevant answers based on the questions, it's proven by the users which they strongly agreed with a weighted mean of 4.6. Furthermore, it is also evident that the chatbot gives clear and easy to understand answers.This means that the chatbot not only gives correct responses but also explains it to the users that can easily be understood and this statement is supported with the users strong agreement with the weighted mean of 4.5. It is also evident that the chatbot helped users find the answers they really need. They strongly agree with a weighted mean of 4.5 that the chatbot's replies were helpful and relevant to the user's questions. Moreover, the users are satisfied with the chatbot's provided information which means it gave complete and very useful answers during their interaction where the users strongly agree in that sense with weighted mean of 4.4. Lastly, the users strongly agree (weighted mean: 4.5) that the chatbot is quick to reply and responded without any delay. This means that the system provides the answers fast, helping users get information they need for research on time. Overall, the respondent users of the chatbot gain an average weighted mean of 4.5 (Strongly Agree). This only mean that users found the chatbot's responses correct, relevant, clear, mostly complete, and that the chatbot responded quickly helping users research fast. This survey therefore shows that responses from students and faculty confirm the effectiveness of the chatbot in its primary function, which is to assists users in finding information to clarify answers within an academic context. For future improvements of the RAG-chatbot, responses should be more complete and slightly faster to further improve overall user satisfaction. Studies of Følstad et al. [2021] they stated that, user-centered evaluation has important role in several disciplines that highlighted modern research on chatbots, especially in understanding users' needs, motivations, and experiences related to the interactions with chatbots. Therefore, an evaluation approach is recommended before deployment of the system, to consider aspects like the effectiveness of the system and user satisfaction. Therefore, this evaluative approach is recommended before system deployment to investigate aspects of system effectiveness and user satisfaction. The result of this user evaluation ensure that the RAG chatbot meets the expectations of real users and provides effective support in tasks related to the retrieval of theses within the CSPC Library context.

User Feedback on RAG chatbot's Effectiveness and Usability

Table 7 presents the results of the user-centered evaluation of the RAG chatbot, using a five-point Likert scale. The result in weighted means for user satisfaction, the likelihood of use in the future, ease of reading and understanding the chatbot's output, and confidence in the information given by the chatbot enable the reader to understand overall user perception and intended future use of the system.

Table 7: User Feedback on RAG chatbot's Effectiveness and Usability

Criteria	Weighted Mean	Verbal Interpretation
Satisfaction with answers	4.3	Satisfied
Likelihood of using the chatbot again	4.3	Very Likely
Ease of understanding the chatbot's output	4.6	Very Easy
Confidence in the chatbot's information	4.1	Confident
Overall Weighted Mean	**4.3**	**Strongly Agree**

The RAG chatbot result whether it is effective and useful are made possible through user responses, summarized in 7, shows that users are very satisfied with answers with a weighted mean of 4.3, we also found that users would likely use the chatbot again in future use case for their research with the weighted mean result of 4.3, the chatbot was also proven to have outputs that are easy to understand by users which they agree with the weighted mean of 4.6. Furthermore, the users are moderately confident in information provided by the RAG-chatbot with the weighted mean result of 4.1. Overall, the respondents of the chatbot's effectiveness and usefulness gain an average weighted mean of 4.3 which means that the chatbot gives what the responses user needs, it also provides clear responses, easy to navigate interface, and a good tool for academic research assistance and retrieval. Based on the studies of Kaushal and Yadav and Okonkwo and Ade-Ibijola supported our findings, highlighting the importance of clarity and usefulness in increasing user satisfaction with chatbots or applications. Further, the researches by Choudhury and Shamszare and Zhang et al. highlight the importance of trust and correct facts to keep users using AI chatbots with confidence in academic purpose. The RAG chatbot has the enormous potential to support academic users, which enhances future use as well as the research process. Nevertheless, the moderate confidence level indicates that the user should look forward to improvements in factual accuracy. Future research should be directed towards improving the validation of information by the chatbot as well as increasing transparency to enhance user confidence to support academic users consistently and dependably.

4 CONCLUSION

In conclusion, finding relevant theses in university libraries such as CSPC remained challenging due to reliance on exact-title or keyword-based search and restrictions on borrowing physical copies. These limitations often required users to visit the library in person and possess prior knowledge of thesis titles, thereby hindering efficient access to academic resources. To address these challenges, this study developed a conversational chatbot utilizing RAG pipeline, enabling users to search thesis documents using natural language queries based on topics or general descriptions. The system processed over 290 undergraduate thesis PDFs through text extraction, chunking, semantic embedding, and indexing in a FAISS vector database. Relevant content was retrieved and augmented with user queries to generate responses using the Gemini 2.5 Flash model, which supported low-latency and multilingual interaction. The chatbot was deployed as a cloud-based web application using Flask, ensuring accessibility anytime and anywhere.

System performance was evaluated using both automated and user-centered approaches. RAGAS evaluation results demonstrated strong retrieval and generation quality, with Context Precision at 0.9167 and Faithfulness at 0.9179 indicating accurate retrieval and reduced hallucinations, while Context Recall at 0.8711 and Answer Relevance at 0.8625 reflected effective coverage and relevance of responses. Additionally, a user-centered survey using a 5-point Likert scale yielded high satisfaction scores, with weighted means of 4.5 for overall response quality and 4.3 for system effectiveness and usability, indicating strong user acceptance and intent for continued use. Although areas for improvement remain, particularly in chunk quality, OCR accuracy, and prompt optimization, the results demonstrated the chatbot's effectiveness in enhancing thesis retrieval and supporting academic research through conversational interaction.

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