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BEYOND LLMS: A RAG CHATBOT FOR EFFICIENT LITERATURE SEARCH AND THESIS RETRIEVAL IN CSPC LIBRARY

A Thesis Project
presented to the Faculty of
College of Computer Studies

In Partial Fulfillment of the Requirements
for the degree Bachelor of Science in Computer Science

By
Divino Franco R. Aurellano
Herald Carl N. Avila
Almira L. Calingacion

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APPROVAL PAGE

In partial fulfillment of the requirements for the degree of Bachelor of Science in Computer Science, this research entitled **BEYOND LLMS: A RAG CHATBOT FOR EFFICIENT LITERATURE SEARCH AND THESIS RETRIEVAL IN CSPC LIBRARY** prepared and submitted by **Divino Franco R. Aurellano**, **Herald Carl N. Avila**, **Almira L. Calingacion** has been examined and is recommended for approval and acceptance.

ROSEL O. ONESA, MIT
Adviser

This research project entitled, **BEYOND LLMS: A RAG CHATBOT FOR EFFICIENT LITERATURE SEARCH AND THESIS RETRIEVAL IN CSPC LIBRARY** in partial fulfillment of the requirements for the degree of Bachelor of Science in Computer Science has been examined and is recommended for acceptance and approval for ORAL EXAMINATION.

RESEARCH COMMITTEE:

KAELA MARIE N. FORTUNO, MIT
Member

TIFFANY LYN O. PANDES, MSc
Member

JOSEPH JESSIE S. OÑATE, MSc
Chairman

PANEL OF EXAMINERS

APPROVED by the Committee on Oral Examination with a grade of **PASSED** on December 9, 2025.

JOSEPH JESSIE S. OÑATE, MSc
Chairman

KAELA MARIE N. FORTUNO, MIT
Member

TIFFANY LYN O. PANDES, MSc
Member

ACCEPTED and **APPROVED** in partial fulfillment of the requirements in Bachelor of Science in Computer Science with a grade of _____.

ROSEL O. ONESA, MIT
OIC Dean, College of Computer Studies

Date: _____

DEDICATION

We, the researchers, dedicate this work to God for giving us wisdom, strength, and perseverance throughout this journey. To our families, whose unconditional love, support, and encouragement have been the foundation of our success, and whose sacrifices and faith in us have made every step possible. To our mentors and instructors, for guiding, challenging, and inspiring us to grow and achieve our goals. To our friends, for their unwavering support, comfort, and laughter, which helped us overcome the challenges along the way. And to our classmates, for sharing this academic journey, offering collaboration, companionship, and memorable experiences that made this chapter meaningful. To all of you who believed in us and supported us in finishing this journey, we sincerely say “thank you.”

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– Team Virgo

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ABSTRACT

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

Authors: Divino Franco R. Aurellano
Herald Carl N. Avila
Almira L. Calingacion

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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.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1

INTRODUCTION

This chapter outlines the study's problem, objectives, and significance. It also defines the scope and limitations, and includes a project dictionary and notes with key terms and supporting details.

Background of the Problem

Large Language Model (LLM) like GPT [2] and Gemini [13] 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 [17, 6]. 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, 12, 18]. Unfortunately, most digitalized libraries today still use outdated search systems that need an exact keyword search, which can result in irrelevant materials [21]. 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.

These challenges of university libraries in the Philippines are shared difficulties in accessing academic resources, outdated search systems, and ineffective information retrieval that affect the efficiency of academic 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 overcome these, Retrieval-Augmented Generation (RAG) has emerged as a superior approach [14]. Unlike standalone LLMs, which require retraining and adding domain-specific data to adjust the LLM weights, RAG presents a state-of-the-art approach that can

retrieve relevant external information to generate responses. It holds a significant practical implications for university libraries that can improve search functionalities. Additionally, RAG ensures that the most relevant academic resources are retrieved quickly and straightforwardly, making it suitable for libraries with extensive collections of academic papers that are difficult for researchers and students to navigate [23, 9].

This thesis developed an enhanced LLM-powered chatbot with the integration of RAG AI framework to improve information retrieval, especially in thesis retrieval of university-owned thesis PDFs at CSPC Library. This chatbot application generates answers and retrieves relevant documents based on the user's prompt.

Statement of the Problem

Finding relevant thesis literature in a University's library, such as in CSPC, can be challenging. Many researchers in the academic community struggle to find the exact thesis paper they need, often requiring them to travel and physically visit the library just to retrieve specific documents.

Currently, CSPC's library website [25] only allows users to search by exact document title. Finding relevant research becomes difficult if users don't know the exact title. What's worst is that library policies restrict researchers from taking thesis books outside the premises, limiting accessibility to research resources. In response to these challenges, this study aims to explore creating a chatbot that eliminates those limitations by enabling searches based on topics, keywords, general descriptions and conversational query. The ultimate goal is to make this tool widely accessible by deploying it on a scalable cloud platform such as Azure.

This goal, by leveraging RAG, this project aims to revolutionize how the academe community interacts with the CSPC library, making research faster, smarter, and more user-friendly.

Objectives of the Study

The objectives of this study are divided into two categories: general and specific. The general objective defines the overall goal of the study, while the specific objectives break down this goal into measurable and achievable steps. These objectives ensure a structured approach to developing an enhanced LLM chatbot for Camarines Sur Polytechnic Colleges.

General Objective

This study aims to develop a chatbot using RAG to revolutionize thesis retrieval and searching in the CSPC Library.

Specific Objectives

To achieve the general objective, the study sets the following specific objectives:

1. To integrate a document ingestion and retrieval module for storing thesis documents.
2. To implement a semantic search and thesis document retrieval system using RAG and Google Gemini.
3. To evaluate the performance of the RAG chatbot using RAGAS and user satisfaction metrics.

Significance of the Study

The result of this study will benefit the following:

Students. This chatbot can help students find campus-relevant research and reduce the time spent on literature review. This will help them to find relevant studies in seconds, without relying solely on exact keywords or titles.

Faculty Members. The system can serve as a research companion for faculty members by providing easier access to all the university's published theses. This can also enhance

their competence in teaching students with thesis writing, academic guidance, and collaborative research work, while at the same time reducing the extent of manual searching for sample published campus theses.

CSPC Library Management. The implementation of a RAG-powered chatbot can revolutionize the library's digital infrastructure, making the academic resources more accessible to users.

Researchers. Current researchers can build on this study to explore the field of AI-driven searching and retrieval. This will add valuable knowledge to the practical applications of RAG.

Future Developers. Future developers can use the findings of this study and use it as a technical reference in AI chatbot implementation in academe.

Scope and Limitation

This study aimed to develop a chatbot for CSPC library, applying RAG framework with Google Gemini LLM. The goal is to address the challenges being faced by the academe community, specifically student researchers in searching and retrieving theses in the library by replacing the current traditional keyword-based search with a more conversational and topic-oriented approach. This will be done through a website with access control, allowing administrators to upload newly published PDF theses and users to register using their CSPC email. Additionally, the system is intended to be deployed to the cloud.

However, there are certain limitations to consider in this study. First, the researchers will focus only on utilizing the available PDF copies of undergraduate theses that have already been published. Second, the chatbot's accuracy can rely on the quality of written info inside the thesis pdf, as well as the clarity and relevance of the user's prompts. Additionally, system performance can be limited to the cloud resources allocated by the researchers given the constraints in budget. This influences the chatbot's real-time processing capacity.

And lastly, while this approach can reduce hallucination, users are still advised to validate the outputs carefully, as occasional inaccuracies or fabricated info may still occur.

Project Dictionary

The Project Dictionary contains the technical terms that defined the conceptual and operation of this study:

- **Academic Literature Retrieval.**The process of systematically searching for and obtaining research documents, to be used in academic work [20]. In this study, the implementation of LLMs is essential to improve the retrieval of available theses documents in CSPC.
- **Chatbot.** Chatbot refers to a conversational agent that is designed to provide assistance, answer queries, and give access to information using natural language and a user-friendly manner [7]. In this study, the chatbot was used to answer questions with human-like responses.
- **Google Gemini**. Google Gemini is a leading multimodal models with advanced reasoning through thinking, long context and tool-use capabilities that can be combined to unlock new agentic workflows like RAG [8]. In this study, Google gemini was used to help the chatbot in reasoning and providing answers based on the long context thesis paper using human-like responses, not limited to English language.
- **Generative AI.** A Generative AI is a subset of artificial intelligence capable of using human language effectively and producing results from carefully designed prompts [5]. In this study, the implications of Gen AI in the context of education and academic integrity were examined.
- **Large Language Models (LLMs).** LLM is an Advanced transformer-based algorithms with billions of parameters that uses attention mechanisms to process massive

datasets and generate coherent, context-aware text [11]. In this study, LLM is used to process hundreds of CSPC thesis PDFs and also worked in the reasoning task.

- **Natural Language Processing (NLP).** NLP is a field of AI that enables computers to understand, work with, and use human language in ways similar to how people talk to each other [19]. In this study, NLP is important for making the RAG pipeline work for users when searching and retrieving theses in CSPC library.

- **Retrieval-Augmented Generation (RAG).** RAG is a language model that takes an input (x), retrieves relevant documents (z), and uses those documents as extra context to produce an output (y) [14]. In this study, RAG was developed for navigating and retrieving information from large amounts of academic papers.

- **Semantic Search.** Semantic Search is an approach in information retrieval that aims to understand the meaning and connections between words, and designed to imitate human understanding [16]. In this study, semantic search will work with RAG in generating relevant and contextual responses.

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CHAPTER 2

RELATED LITERATURE AND STUDIES

This chapter reviews related literature and existing systems on the study. It provides a synthesis of related works, an overview of state-of-the-art technologies and methodologies, and underline the research gaps that the present study has addressed.

Review of Related Literature and Studies

A review of books, scholarly articles, journals, and previous thesis projects concerning the research topic was carried out to develop an in depth understanding of the subject of the study. The findings are organized thematically in line with the key areas of the study.

Large Language Models

Large Language Models (LLMs) have significantly improved the use case of information retrieval (IR) within academic settings. The integration of LLMs, like ChatGPT and other model architectures, offers notable advancements in natural language processing (NLP) and also proves its capabilities to enhance IR, question-answering, summarization, and content generation, which benefits academic environments where efficient access to information is crucial [21, 22]. Recent works by Khraisha et al. [2024] and Gartlehner et al. [2023] have demonstrated how large language models can automate research tasks such as systematic review, data extraction, and document screening. This suggests that LLMs are capable of improving research productivity in academia [12, 9].

Even though LLMs offer a number of advantages with regard to information retrieval, they also present significant challenges. Among the major challenges is that they are inefficient at executing domain specific tasks for which specialized knowledge is required.

This is because these models source knowledge from pre-training, hence LLMs are limited to offer fact based responses within certain domains such as academia. Omar et al. mentioned in their study that LLMs, including ChatGPT, could be helpful in specialized domains to serve complementary purposes but may fail in complicated queries because they have not seen enough training data related to those fields [12]. Moreover, pre-trained LLMs have difficulty keeping on pace with continuous data growth in various domains, thus, it is impossible for them to refresh their knowledge without extensive fine-tuning. Lucas et al. point out that this inability-in an academic and professional sense-of large language models to access up-to-date domain-specific repositories significantly diminishes their effectiveness and value [9].

Despite of LLMs being at the lead of NLP innovation, their actual application in domain-specific tasks is deeply prevented by certain challenges. These include real-time data availability, dependence on pre-trained knowledge bases, and ethical concerns pertaining to data privacy. Innovation around these challenges using novel methodologies, such as the retrieval-augmented generation approach, increases the capability of models to meet specialized applications that have strict requirements.

Retrieval-Augmented Generation

RAG has achieved remarkable improvements in the IR domain, especially in tasks regarding literature search and thesis retrieval in library systems [20]. The architecture supports the traditional large language models with external knowledge sources for enhancing the relevance, richness, and correctness of the responses [7].

As articulated in the studies of Lewis et al. [2020] titled ”Retrieval-Augmented Generation for Knowledge Intensive NLP Tasks,” RAG provides for much more accurate responses because it helps in addressing certain inherent limitations of LLMs, especially in the areas of accurate knowledge retrieval and context relevance. Another academic study about the topic is the the study of Shuster et al. [2021], titled ”Retrieval Augmentation

Reduces Hallucination in Conversation," go on to show that RAG reduces inconsistencies and hallucinations in the LLM outputs. Their results show that RAG mechanisms increase conversational fluency and integrity, particularly in open domain conversational settings, bringing about knowledgeable and more coherent responses.

Moreover, it has recently been further supported by work titled "GENAI: RAG Use Cases with Vector DB to Solve the Limitations of LLMs," in which the authors demonstrate that the integration of vector databases with RAG essentially improves retrieval speed and relevance. Semantic search using vector databases makes continuous real-time updates possible for dynamic domains such as business and academic libraries, resulting in a high level of knowledge management and factual correctness in the generated responses. Thus, RAG strengthens not only the capability of LLM retrieval but also addresses the essential weaknesses of LLMs: consistency and factuality [16].

Document Ingestion and Retrieval

Successful execution of RAG systems relies on utilizing documents in an effective manner and carrying out robust retrieval procedures, particularly in addressing large and complex datasets found in academic libraries. RAG systems can use any data source, including text, video, images, and audio, thus allowing flexible and contextually rich information retrieval. In study this about RAG, the main corpus mostly used is PDF documents to extract academic content which focuses by this authors [14].

The RAG chatbot rely its effectiveness by depending on the quality of preprocessing, which involves converting unstructured PDF data into machine readable formats suitable for embedding and semantic search [5, 4]. The PyPDF2, PyMuPDF, and pypdfium are the commonly used tools for this task in most studies to help in extracting raw text from complex PDF layouts [1].

A study by Sagi [2024], "GENAI: RAG Use Cases with Vector DB to Solve the Limitations of LLMs," further corroborates this idea by showing how the introduction of vector

databases significantly improves retrieval speed and relevance when integrated into RAG. The semantic search capabilities of the vector databases in turn support continuous real-time updates in dynamic domains like academic and business libraries, hence greatly improving knowledge management and factual accuracy of responses generated.Therefore, RAG enhances not only the retrieval capabilities of LLMs but also considerably mitigates its traditional deficiencies in consistency and factual accuracy [16].

Adhikari and Agarwal [2024] into their examined different kind of PDF parsers using F1 score, BLEU-4, and local alignment on a wide range of document types. The results show that PyMuPDF and pypdfium more reliable to retain sentence structure and format than the other tools, something highly recommended for retaining semantic coherence and offering proper vectorization and retrieval. One can also observe parsing difficulties posed by complex documents, such as scientific articles and patent PDFs, for which rule-based tools significantly underperform versus transformer-based models [1].

As stated out by Zhang et al. [2023], automated ingestion pipelines parsing documents into a searchable database improve the discoverability and access to scholarly content.

Techniques like OCR, metadata extraction, and structured indexing are common practices employed on thesis repositories to enable various retrieval operations easily [23]. Along related lines, Karpukhin et al. [2020] stress the importance of document preprocessing, chunking, and embedding to permit semantic search in DPR and, consequently, for modern RAG [11]. Generally, this ingestion process consists of several steps: (1) extracting text with PyMuPDF or pypdfium, among other tools; (2) chunking the text into smaller, logically coherent pieces; and (3) embedding by models such as Sentence-BERT. Later, these vectors will be kept in specialized vector databases (e.g., FAISS, Pinecone) so that the actual retrieve action when users make inquiries will be fast and efficient. Hence, robust document ingestion and storage directly impact retrieval accuracy, system responsiveness, and user experience. Taking as its basis on Sagi's study, it is clear that effectiveness in ingestion and vectorization yields fast retrieval of relevant information and generates very

high accuracy, context enriched responses from RAG models, particularly within domain like academic libraries [11].

The authors in Deepak et al. [2025], ”LangChain-Chat with My PDF”, present the prevalent workflow for processing PDFs, which is focused on embedding and chunking within the general techniques of vectorization. This work illustrates how chunking enables RAG to retrieve the most relevant document segments in order to answer user queries and hence better handle long PDF enhancing search capabilities within the system [8].

Taken together, these works suggest that perfectly done preprocessing, data ingestion, and vectorization form is crucial for bridging static document repositories with real-time information retrieval, demonstrating the potential for RAG architectures in managing large collections of academic knowledge [2, 4].

RAG Applications in Various Domains

Beyond contexts in the field of academics, RAG frameworks are increasingly applied to specialized domains, including legal research, medical information retrieval, and scientific literature search, underlining broad versatility and impact.

In the academic domain, Grigoryan and Madoyan [2024] proposed a solid foundation for future advancements in academic information retrieval through their study ”Building a Retrieval-Augmented Generation (RAG) System for Academic Papers,” creating a RAG system that retrieves and analyzes a vast amount of academic papers. They used vector search techniques like cosine similarity and HNSW indexing on the paper’s abstracts and full texts to pass only relevant information to LLM, which significantly enhanced the retrieval and generation [10]. This was also supported by Aytar et al. [2024], that proposed enhanced RAG architecture for academic literature navigation in data science, introducing their approached of semantic chunking and an Abstract-First strategy, which significantly enhances the capability of RAG to retrieve pertinent academic content. [6].

In the healthcare domain, As Arzideh et al. [2024] point out, using domain specific

clinical embeddings makes the RAG approach highly effective. Their work, "MIRACLE-Medical Information Retrieval using Clinical Language Embeddings for Retrieval Augmented Generation at the Point of Care," have enhances clinical decision making, improves workflows in documentation, and personalizes access to health information. Supporting this, Amugongo et al. [2024] note that the RAG architecture is able to retrieve external medical data in a very effective manner, thus providing responses with high levels of accuracy and reliability while minimizing the limitations characteristic of traditional LLMs.

Similarly, in the legal domain, a study by Aquino et al. [2024] notes that RAG systems greatly enhance legal research by speeding up the retrieval of cases and statutes and enhancing the authenticity and contextual accuracy of the output.

In conclusion, these studies collectively show that RAG has already been applied on various domains, from academic research to other specialized fields. Majority of the findings highlights that by using various techniques within the RAG architecture can enhance any domain-specific tasks in a way that traditional LLM cannot achieve.

Evaluation of Retrieval-Augmented Generation (RAG) Systems

Evaluation of RAG systems requires methodological extensions beyond those applied in traditional designs for large language models. The RAGAS framework presents a structured way of evaluating the context precision, contextual relevance, and faithfulness in a generated response. Studies of Shuster et al. [2021] shows that high quality retrieval has a great effect on user satisfaction and perceived reliability with respect to conversational AI. This, therefore, underlines the need for specialized evaluation frameworks which can guarantee the effectiveness of RAG systems.

In specialized needs, metrics tailored for RAG models come into pivotal consideration. One of the widely used approaches is the RAGAS evaluation framework that provides key metrics such as Context Recall, Faithfulness, and Response Relevance. These metrics assess the degree to which the retrieved documents substantiate the generated response [15].

Context Precision characterizes the share of relevant chunks inside the contexts retrieved, while Context Recall ensures that no important information is missed. Faithfulness checks factual coherence between generated responses and the respective retrieved documents, while Response Relevance checks if the response correctly addresses user query [4] [8].

However, while automated measures may be more valid for some purposes, they often lack coverage of the qualitative dimensions of consistency, fluency, and overall user satisfaction. Human evaluation, according to Sivasothy et al. [2024], is necessary in improving these systems, since it considers factors that the automated approaches may fail to address.

Synthesis of the State-of-the-Art

The related literature and systems discussed have substantial relevance to the problem of the study. To have a clear understanding of this literature and studies, the researchers made a synthesis in the succeeding discussions.

LLM with integrated RAG techniques have greatly improved the knowledge-intensive NLP tasks, overcoming LLMs' challenges. The studies of Thapa et al. [2022] and Thomo [2024] on how combining RAG with LLMs significantly improves accuracy and coherence in conversations and complex queries. The advantage of this technique enables LLMs to retrieve relevant external data, reducing hallucinations and improving factual consistency [19, 20]. Furthermore, Lewis et al. [2020] discussed the application of vector databases for continuous integration with RAG, which shows a significant improvement in both retrieval efficiency and the relevance of output produced by large language models . This topic plays a major role in literature searching and retrieving theses from university libraries [13].

A collection of various studies compiled on the use of RAG in different domains is discussed below. For instance, Arzideh et al. [2024] incorporated clinical language embeddings into RAG for better healthcare information [5]. Grigoryan and Madoyan [2024], in "Building a Retrieval-Augmented Generation (RAG) System for Academic Papers,"

proposes a system that augments academic retrieval through vector search [10]. Further, Aquino et al. [2024] used RAG on the effective extraction and analysis of Brazilian legal [4]. Together, these reports illustrate the adaptability of RAG and its potential to transform how university libraries search for and provide access to academic theses.

Evaluation metrics are important for evaluating the performance of RAG in retrieving and generating accurate responses. Specific metrics of RAGAS, such as Context Precision, Faithfulness, and Answer Relevance, as emphasized in the studies of Sagi [2024] and Arzideh et al. [2024], ensure the authenticity and consistency of the generated outputs of the model [16, 5]. Despite the effectiveness of automated metrics, human evaluation remains important to assess coherence and user satisfaction, as mentioned in this study [4].

In summary, RAG integrated with LLMs presents a groundbreaking method for improving literature searches and thesis retrieval in university libraries, especially at CSPC library. Through testing the limitations and obstacles faced by traditional LLMs, the integration of RAG reveals its promise to transform research accessibility at the CSPC library.

Gap Bridge of the Study

Existing literatures has explored the applicability of RAG in domains from academic research to other specialized fields, it is concerning to note that there's a gap in the way of specific applications of these systems to academic libraries for enhancing literature searches and thesis retrievals. While previous studies have shown how well RAG improves information retrieval, not much has been done in applying this within university libraries, where there is a unique challenges and requirements that such implementations needed.

This study tries to fill this gap by designing a RAG-based chatbot system specific to the CSPC library. By focusing on the unique challenges and demands of academic libraries, this paper seeks to add substantial value in understanding the appropriate application of RAG systems toward improvement of information retrieval.

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CHAPTER 3

METHODOLOGY

This chapter discusses the specific steps and logical procedures that were employed to develop and evaluate the RAG-based LLM chatbot system. This includes the research design, theoretical and mathematical framework, software and hardware tools, instruments, procedures, evaluation metrics, and a conceptual framework.

Research Design

Constructive research approach focuses on producing innovative constructions that intend to solve real-world problems and contribute to the theory of the discipline in which it is applied. This methodology is particularly well-suited to fields like information systems and artificial intelligence, where the goal is not only theoretical insight but also the creation of innovative, functional systems [7].

This study adopted a constructive research design to develop a library chatbot using RAG for CSPC. 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.

By adapting a constructive design, the researchers were able to build on existing methodologies while innovating and establishing a new solution that addressed the specific challenges in the current search and thesis retrieval in CSPC. By combining the existing infor-

mation within the tailored architecture, this study contributed to the demanding research on LLMs and RAG being used in various domains, such as education and research discovery.

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.

Retrieval-Augmented Generation (RAG) Pipeline

The 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.

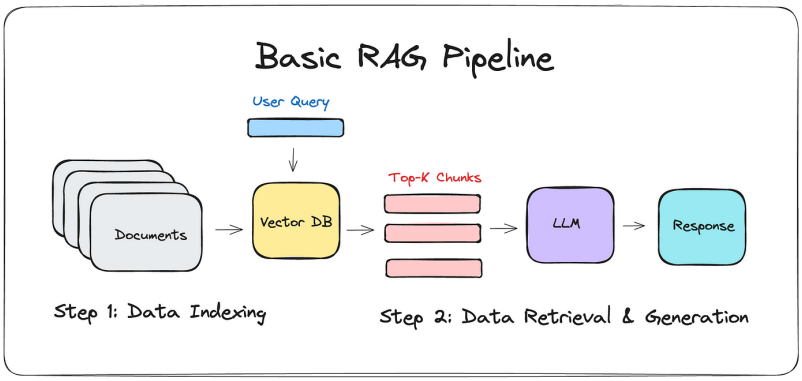

Figure 1: **Basic RAG Pipeline by Dr. Julija**

The RAG pipeline as illustrated in Figure 1, consists of the following key stages:

A. Data Indexing

The process begins with data loading, where all needed thesis documents are imported to be utilized. Considering that every thesis documents are large document composing of hundreds of pages, these were splitted into smaller chunks using a token-based method

that respects academic structure (Abstract; Chapters 1–5). Each chunk is then converted into a vector using the open-source ‘sentence-transformers/all-MiniLM-L6-v2‘ embedding model from Hugging Face, which was chosen for its lightweight architecture and strong semantic representation capabilities. Lastly, the data storing, where vector embeddings and their associated metadata were stored in FAISS for efficient similarity search.

B. Retrieval and Generation

This stage is where the chatbot creates an action that addresses the challenge. It begins when a user starts to query, and that query was embedded using the same model (sentence-transformers/all-MiniLM-L6-v2) used from the first stage. That embedded query was used by FAISS retriever to perform a semantic search matching from the vector database. The parameter on Top-K most relevant chunks was set as default K =50, to balance precision and recall. And finally, during generation, these retrieved chunks are fed to the Google Gemini 2.5-flash language model as grounded context to create a human-like response.

Large Language Model

Based on the study of Naveed [2024], LLMs have demonstrated remarkable performance in challenges related to NLP and beyond. These were also considered as cutting-edge AI systems trained on massive datasets to process and generate text and can excel in tasks such as summarization, question answering, and retrieval [11].

Gemini 2.5-flash

Specifically, the llm that was used in this project is Gemini 2.5 Flash, part of the Gemini 2.X model family introduced by Comanici et al. [2025]. It gives advanced reasoning capability at a lower compute resource, low latency and cost. This family also top-ranks in the llms that have multimodal support and extended context windows [2]. By incorporating it into this project, it can enhance thesis retrieval tailored for CSPC library users.

Materials and Statistical Tools / Evaluation Methods

To ensure optimal performance of the RAG-based LLM system, several key hardware and software components are required.

Research Materials

This section includes the dataset that was used, as well as the minimum hardware and software needed for the development of the system.

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

To support the development of the RAG chatbot, the researchers used hardware components that meet or exceed the specifications listed in Table 1. These components were selected to ensure a smooth ingestion and embedding process of the large pdf dataset.

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)

The researchers considered using a modern multi-core CPU to enable efficient data processing and high inference. Sufficient memory was also crucial; At least 16 GB of RAM is recommended and is the least to manage large-scale ingesting and embeddings. A 1 TB SSD was preferred to use due to its high read/write speeds, which help in the indexing process, and also serves as the data storage for thesis PDF documents. Considering also that LLM embeddings are resource-intensive when used, a powerful GPU like NVIDIA RTX 3090 or a higher version was recommended to speed up deep learning inference and vector operations.

Software

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

Python serves as the core programming language due to its strong support for ML and NLP. While version 3.10 or later was used as the latest stable version, this may vary if there's a new update. FAISS from Facebook was utilized as the vector database for its fast vector similarity search and compression. The Gemini 2.5-flash LLM called from

Google Generative AI API serves as the reasoning model for the chatbot, and the sentence-transformers/all-MiniLM-L6-v2 from Hugging Face was used as the embedding model that transformed chunks into vector embeddings. While the Flask framework was used to build the whole system for its simplicity.

Various modules was also called to help in document parsing and extraction. One is through PyMuPDF for text extraction from thesis PDF files. NumPy for numerical operations and help a lot in the evaluation, and the LangChain framework manage the orchestration of LLMs during query interpretation and response generation.

Instrument

In this subsection, the instruments that was used by researchers to analyze and evaluate the performance of the RAG chatbot system.

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 [10]. Furthermore, a context recall metric was included, as recommended for evaluating retrieved chunks.

Survey. Instruments served as data collection tools across different areas and provided an effective way to gather information. They were useful when seeking insights into the attributes, preferences, opinions, or beliefs of a specific group. To meet the study objectives, 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, the researchers created a questionnaire 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.

Statistical Test

The RAG system performance was evaluated using the RAGAS framework, focusing on context precision, recall, relevance, and faithfulness to measure how well relevant documents were retrieved and responses generated [4, 1, 6]. Additionally, to assess not only the technical but also the user-centered performance of the system, a user questionnaire was administered to collect feedback regarding usability, accuracy, and overall satisfaction.

The Likert Scale, introduced by Likert [1932], is a measurement method for evaluating individuals' attitudes toward any object. In particular, the 5-point Likert Scale was chosen because it works well in surveys and requires less time and effort to develop [5, 9].

Table 3
Likert Scale for User Level of Agreement

Scale	Range	Level of Agreement	Description
5	4.21 - 5.00	Strongly Agree	The participant strongly supports or agrees with the chatbot's response.
4	3.21 - 4.20	Agree	Implies a positive stance toward the chatbot's response.
3	2.61 - 3.20	Neutral	The respondent has neither a positive response nor a negative response, but undecided denotes a state of confusion of the respondent.
2	1.81 - 2.60	Disagree	Suggests a level of disagreement with the statement or question, but not as strong as Strongly Disagree.
1	1.00 - 1.80	Strongly Disagree	Indicates a strong and definitive disagreement with the statement or question. The respondent strongly opposes or disagrees with the chatbot's response.

Table 3 shows that this study employed a 5-point Likert Scale to determine "User level of Agreement" based on the user's experience with the system's response quality and per-

formance. In the table, the first column showed the scale, and the second is its equivalent range, then the scale that the system level of agreement fell under was shown in the third column, and with its corresponding description in the fourth column. The user's response was computed using the weighted mean statistical method, and then it was determined in which range it fell.

The scale is the numerical value that corresponds to the level of agreement (Strongly agree, agree, neutral, disagree, strongly disagree). This is important as it allows it to be used in statistical analysis. Scale 5 with a range of 4.20 - 5.00 described as "Strongly Agree", which means that the users who tested the chatbot completely agreed with the described criteria or considered its quality and performance excellent. Scale 4 with a range 3.40 - 4.19 described as "Agree", shows that the user who tested the chatbot generally agrees with the described criteria, but not to the strongest extent. The Scale 3 with a range of 2.60 - 3.39 was described as "Neutral", meaning that the user of who tested the chatbot is neutral, undecided, or the criteria description doesn't strongly resonate in either direction. Scale 2 with a range of 1.80 - 2.59 described as "Disagree", denoting that the user who tested the chatbot disagrees with the criteria description but not as intensely as "Strongly Disagree". And lastly, Scale 1 was described as "Strongly Disagree", meaning that the user who tested the chatbot completely disagrees with the criteria description or finds the system to be low quality and low performance.

Another set of questionnaires was prepared to determine the level of user satisfaction, likelihood of using the application in the future, ease of reading and understanding chatbot output, and confidence in response information regarding the RAG chatbot system. User opinions are expected to provide an understanding of the overall user experience and satisfaction level with the chatbot's performance in thesis retrieval tasks and its accessibility that proposed to solve the problem. A Likert scale-type questionnaire was also used for this purpose, employing the same 5-point scale framework to ensure consistency in measurement and analysis as shown in Table 4.

Table 4
User Level of Satisfaction with Answers

Scale	Range	Level of Satisfaction	Description
5	4.21 - 5.00	Very Satisfied	The participant is very satisfied with the chatbot's answers.
4	3.21 - 4.20	Satisfied	Indicates a positive satisfaction toward the chatbot's answers.
3	2.61 - 3.20	Neutral	The respondent has neither a positive nor negative satisfaction; undecided or indifferent denotes a state of uncertainty of the respondent.
2	1.81 - 2.60	Unsatisfied	Suggests a level of dissatisfaction with the chatbot's answers, but not as strong as Very Unsatisfied.
1	1.00 - 1.80	Very Unsatisfied	Indicates a strong and definitive dissatisfaction with the chatbot's answers. The respondent is very unhappy with the chatbot's responses.

Table 4 shows that RAG chatbot system used 5-point Likert Scale to determine users Level of Satisfaction based on the user's experience to the system's answers. The first column showed the scale that the system level of satisfaction fell under which was shown in third column and its corresponding definition in the fourth column. User's response would be computed using weighted mean and was determined in which range fell under. Scale 5 with a range of 4.20-5.00 described as "Very Satisfied" which means that the user of the RAG Chatbot completely satisfies with the provided answers, scale 4 with a range 3.40-4.19 described as "Satisfied", the user of the RAG Chatbot is satisfied with the provided answers but not to the strongest extent, scale 3 with a range 2.60-3.39 described as "Neutral", the user of the RAG chatbot is neutral, undecided, or the criteria description doesn't strongly resonate in either direction, Scale 2 with a range of 1.80-2.59 described as "Unsatisfied", the user of the RAG Chatbot is unsatisfied with the provided answers but not as intensely

as “Very Unsatisfied”, and Scale 1 is described as “Very Unsatisfied”, the user of the RAG chatbot completely dissatisfied with the provided answers.

Table 5
Likert Scale for User Level of Using the Chatbot Again

Scale	Range	Level of Using the Chatbot Again	Description
5	4.21 - 5.00	Very Likely	The participant is very likely to use the chatbot again.
4	3.21 - 4.20	Likely	Implies a positive intention to reuse the chatbot.
3	2.61 - 3.20	Neutral	The respondent is undecided or indifferent about using the chatbot again.
2	1.81 - 2.60	Unlikely	Suggests a low intention to reuse the chatbot, but not as strong as Very Unlikely.
1	1.00 - 1.80	Very Unlikely	Indicates a strong and definitive intention not to use the chatbot again. The respondent is very unlikely to reuse the chatbot.

Table 5 shows that RAG chatbot system used 5-point Likert Scale to determine users Level of Using the Chatbot Again based on the user’s intention to reuse the system after their experience. The first column showed the scale that the system level of reuse fell under which was shown in third column and its corresponding definition in the fourth column. User’s response would be computed using weighted mean and will be determined in which range fell under. Scale 5 with a range of 4.20-5.00 described as “Very Likely” which means that the user of the RAG Chatbot is very likely to use the system again or finds it highly useful, scale 4 with a range 3.40-4.19 described as “Likely”, the user of the RAG Chatbot is likely to use the system again but not to the strongest extent, scale 3 with a range 2.60-3.39

described as “Neutral”, the user of the RAG chatbot is neutral, undecided, or the criteria description doesn’t strongly resonate in either direction, Scale 2 with a range of 1.80-2.59 described as “Unlikely”, the user of the RAG Chatbot is unlikely to use the system again but not as intensely as “Very Unlikely”, and Scale 1 is described as “Very Unlikely”, the user of the RAG chatbot is very unlikely to reuse the system or finds it not useful enough to return.

Table 6
User Level of Understanding Chatbot Responses

Scale	Range	Level of Understanding	Description
5	4.21 - 5.00	Very Easy	The participant finds the chatbot’s responses very easy to understand.
4	3.21 - 4.20	Easy	Implies generally easy comprehension of the chatbot’s responses.
3	2.61 - 3.20	Neutral	The respondent neither finds the responses easy nor difficult; undecided denotes a state of ambivalence.
2	1.81 - 2.60	Difficult	Suggests some difficulty in understanding the chatbot’s responses, but not as severe as Very Difficult.
1	1.00 - 1.80	Very Difficult	Indicates the participant finds the chatbot’s responses very difficult to understand.

Table 6 shows that RAG chatbot system will use 5-point Likert Scale to determine users Level of Understanding based on the user’s ease in reading and comprehending the system’s responses. The first column showed the scale that the system level of understanding fell under which was shown in third column and its corresponding definition in the fourth column. User’s response would be computed using weighted mean and will be determined in which range fell under. Scale 5 with a range of 4.20-5.00 described as “Very Easy” which means that the user of the RAG Chatbot finds the chatbot’s responses very easy to under-

stand or finds its clarity and readability excellent, scale 4 with a range 3.40-4.19 described as “Easy”, the user of the RAG Chatbot finds the responses easy to understand but not to the strongest extent, scale 3 with a range 2.60-3.39 described as “Neutral”, the user of the RAG chatbot is neutral, undecided, or the criteria description doesn’t strongly resonate in either direction, Scale 2 with a range of 1.80-2.59 described as “Difficult”, the user of the RAG Chatbot finds the responses difficult to understand but not as intensely as “Very Difficult”, and Scale 1 is described as “Very Difficult”, the user of the RAG chatbot finds the responses very difficult to understand or considers the system unclear and hard to interpret.

Table 7
Likert Scale for User Level of Confidence on Information Received

Scale	Range	Level of Confidence	Description
5	4.21 - 5.00	Very Confident	The participant is very confident in the information received from the chatbot.
4	3.21 - 4.20	Confident	Implies a general confidence in the chatbot’s information.
3	2.61 - 3.20	Neutral	The respondent neither expresses confidence nor distrust; undecided denotes a state of uncertainty of the respondent.
2	1.81 - 2.60	Unconfident	Suggests some lack of confidence in the chatbot’s information, but not as strong as Very Unconfident.
1	1.00 - 1.80	Very Unconfident	Indicates a strong and definitive lack of confidence in the chatbot’s information. The respondent is very unconfident about the chatbot’s responses.

Table 7 shows that RAG chatbot system used a 5-point Likert Scale to determine users Level of Confidence based on the user’s trust and perceived accuracy of the information retrieved by the system. The first column showed the scale that the system level of confidence was classified as, which was shown in third column and its corresponding description in

the fourth column. User's response would be computed using weighted mean and will be determined in which range fell under. Scale 5 with a range of 4.20-5.00 described as "Very Confident" which means that the user of the RAG Chatbot is very confident in the information received or finds its accuracy and reliability excellent, scale 4 with a range 3.40-4.19 described as "Confident", the user of the RAG Chatbot is confident in the information but not to the strongest extent, scale 3 with a range 2.60 - 3.39 described as "Neutral", the user of the RAG chatbot is neutral, undecided, or the criteria description doesn't strongly resonate in either direction, Scale 2 with a range of 1.80-2.59 described as "Unconfident", the user of the RAG Chatbot lacks confidence in the information retrieved but not as intensely as "Very Unconfident", and Scale 1 is described as "Very Unconfident", the user of the RAG chatbot is very unconfident in the chatbot's information or finds the responses unreliable.

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 the chatbot 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:

$$WM = \frac{TWM}{N} \tag{3.1}$$

Where:

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

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** - The collected PDF thesis documents underwent text extraction, cleaning, and chunking. This stage, along with the next, is done in a separate Python notebook to support visualizations.

   (a) Text Extraction: The PyMuPDF was used to extract text from the PDF files. This is useful for converting the pdf to a structured Markdown language.

   (b) Cleaning: Data cleaning was employed since the thesis structure is somewhat messy and has redundant or non-informative characters and formatting. One example is headers that appear on every page were extracted at first, but removed.

   (c) Text Chunking: Since every thesis document is composed of hundreds of pages and thousands of text, these were divided into smaller, manageable chunks.

2. **Indexing and Vector Embedding** - In this stage, the preprocessed chunks were transformed into vector representations and indexed for efficient retrieval.

   (a) Vector Embedding: Each text chunk was embedded using sentence-transformers/all-MiniLM-L6-v2 from Hugging Space.

   (b) Data Storing: FAISS then stored the vectors along with metadata such as document titles, authors, and section headers.

3. **Query Handling and Semantic Retrieval** - User queries need to be understandable not just by human but also by computers. Also, it should be compatible with the

stored vectors from the previous indexing. This step vectorized the user query using the same embedding model to be compared using similarity search in retrieving relevant chunks from the FAISS database.

(a) Query Encoding: The user query is transformed into a high-dimensional vector using the same embedding model applied in indexing. Guard rail was also applied to prevent unethical output of the system.latent space.

(b) Similarity Search: That vectorized query then matched against stored vectors from the FAISS to retrieve the top-K relevant chunks, with default K set to 50. This K also have a conditional parameter set in the code allowing it to adaptively increased to 100 for exhaustive searches.

4. **Response Generation** - Gemini 2.5-flash language model effectively processed the augmented input to generate a human-like response. This choice supports multimodal language and low-latency response generation at a low cost.

5. **Output Presentation** - Using the Flask web framework, the system displayed the generated response through a ChatGPT-styled user interface, which most of the time includes the title, summary, and URL of the thesis for full accessibility.

6. **Performance Evaluation**

(a) Automated Evaluation: Metrics from the RAGAS framework such as Context Precision, Context Recall, Answer Relevance, and Faithfulness, were used to evaluate model performance. The RAGAS is one of the most used evaluation framework in RAG architectures due to its fast evaluation cycle [3].

(b) Human Evaluation: A usability questionnaire was distributed to a sample of student users to assess the system's clarity, ease of use, and usefulness in retrieving academic information.

Evaluation Metrics

Researchers evaluated the performance of the RAG-Based System using the RAGAS[3], which focusing on context precision, context recall, response relevance, and faithfulness. With these metrics, it will evaluate retrieval accuracy, quality, query similarity, and factual grounding of generated answers, ensuring that system produces reliable and useful outputs for users.

Context Precision

Context Precision metric was used to evaluate the retrieval value of the RAG chatbot within the CSPC Library. It measured the amount of relevant document chunks among the top K retrieved results, that emphasizing the system's ability to present highly relevant content at higher ranks. A higher Context Precision specify that the system effectively prioritized relevant information for the user.

$$\text{Context Precision@K} = \frac{\sum_{k=1}^{K} (\text{Precision@k} \times v_k)}{\text{Total number of relevant items in the top } K \text{ results}} \tag{3.2}$$

where Precision@k denotes the precision at rank k, and v_k is a binary indicator variable such that $v_k = 1$ if the chunk at position k is relevant, and $v_k = 0$ otherwise. The K indicates the cutoff for the top results evaluated, while the denominator was the one that normalizes the metric by considering the total number of relevant items within the top K retrieved results. This weighted approach helped so that relevant items retrieved earlier in the ranking will contribute more to the final score, making the metric meaningful for library retrieval tasks.

The precision at each position k, denoted as Precision@k, was calculated using this equation:

$$\text{Precision@k} = \frac{\text{true positives@k}}{\text{true positives@k} + \text{false positives@k}} \tag{3.3}$$

where true positives@k is the number of relevant chunks retrieved up to position k, while the false positives@k was the number of non-relevant chunks that was retrieved up to the same position. This metric calculates retrieval accuracy at each rank and serves as the main basis for the overall Context Precision@K calculation.

Context Recall

Context Recall was used to evaluate the comprehensiveness of the retrieval system in capturing all relevant information necessary to answer a query. In this study, It measured the amount of relevant chunks successfully retrieved by the RAG system within its knowledge base.

$$\text{Context Recall} = \frac{\text{Number of relevant claims supported by retrieved chunks}}{\text{Total number of relevant claims in the reference answer}} \tag{3.4}$$

where:

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

This metric show how effectively the system provides the necessary knowledge, with a value ranging between 0 and 1, where 1 specify the perfect recall. It ensures that important academic information is not missed during retrieval, making it an essential part of evaluating the RAG system.

Response Relevance

The response relevance was a crucial metric that was used to evaluate how relevant was the response RAG system in answering the specific query asked by the user. This metric works by penalizing responses that are either incomplete or contains unnecessary detail.

$$\text{Response Relevance} = \frac{1}{N}\sum_{i=1}^{N}\cos(E_{g_i}, E_o) \tag{3.5}$$

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 obtain from the response,
- E_o is the embedding of the user query,
- $\cos(E_{g_i}, E_o)$ represents the cosine similarity between the generated question embedding and the original query embedding.

This metric was based on the idea that if the chatbot's response correctly answered the original query, then questions generated from that response would semantically similar with the original question. This involved generating multiple artificial questions, and also embedding both the response-generated questions and the original query into vector embeddings. The mean cosine similarity was then calculated to measure the alignment, so that the retrieved academic information will closely match the research needs of the users.

Faithfulness

The Faithfulness is a critical metric for evaluating the consistency of the RAG chatbot's that generates responses with the retrieved context from the CSPC Library. This metric was

used so that all claims made in the chatbot's answer are directly supported by the information present in the retrieved documents, thereby reducing hallucinations and maintaining academic integrity.

$$\text{Faithfulness} = \frac{\text{Number of claims in the response supported by retrieved context}}{\text{Total number of claims in the response}} \tag{3.6}$$

where:

- *Number of claims in the response supported by retrieved context* refers to the count of factual statements in the generated answer that can be directly verified or inferred from the retrieved context chunks.
- *Total number of claims in the response* is the complete count of all factual statements made in the answer, even so whether they are supported by the context. A faithfulness score of 1.0 shows that all claims in the response are grounded in the retrieved context, while lower scores reveal the presence of unsupported or hallucinated.

A faithfulness score of 1.0 indicates that all claims in the response are grounded in the retrieved context, while a lower score means that hallucination has occurred. In this study, a high faithfulness result is crucial so that the RAG system's generated answers are factually correct and grounded in the thesis chunks.

Conceptual Framework

This section presents the conceptual framework adapted in the study. This serves as the foundational blueprint for the RAG chatbot. As illustrated in Figure 2, the system followed a cyclical process starting from data collection and ending with performance evaluation. The arrows were used to indicate the step-by-step flow of each component within the

framework; note that these did not signify any technical operation or special relationship beyond showing the direction of the process.

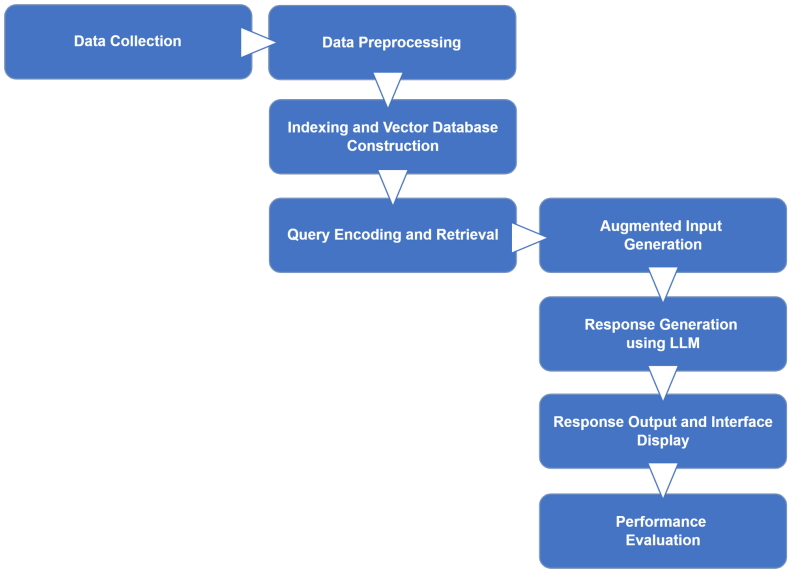

Figure 2: **Conceptual Framework of the RAG-Based Chatbot System**

Data Collection. The process began when the researchers started coordinating with CSPC Library, where the prototype was demonstrated to show how RAG chatbot could improve searching, specifically in thesis retrieval. In the demonstration, the project's institutional value was emphasized in revolutionizing access to information, as well as addressing the pain points for the researchers. Following that was the researchers' formal request to gain access to all available thesis PDFs from various College departments of CSPC to use as the main corpus of the proposed RAG system.

Data Pre-processing. PyMuPDF was used to extract text from the collected PDFs and then convert it to markdown. The extracted content underwent data cleaning to remove redundant and non-informative characters, and was followed by a token-based chunking strategy.

Indexing and Vector Database Construction. Each chunk was embedded using the sentence-transformers/all-MiniLM-L6-v2 model from Hugging Face, converting it into

dense vectors that capture semantic meanings. These vectors were stored in a FAISS vector database for fast and efficient similarity search. Moreover, metadata was also stored for each document. This construction was research-proven, surpassing traditional keyword-based searching.

Query Encoding and Retrieval. In this part, when the user started to query, those queries were encoded into dense vectors using the same embedding model used in indexing. The system then performed a similarity search in FAISS, retrieving the top-K relevant chunks.

Augmented Input Generation. In this study, the augmented input generation phase served as the bridge between retrieved thesis content and response generation. This is where the retrieved top-k chunks are combined with the user query to guide the reasoning model in generating an answer.

Response Generation, This stage is where the reasoning model takes its action. For this, Gemini 2.5 flash generates a tailored response based on the augmented input. Choosing this model enables a late latency response and multimodal support that can even understand the local language of CSPC students.

Response Output and Interface Display. Web frameworks such as Flask and Django are commonly used to develop chatbot web applications. These frameworks provide complete tools and libraries for building web applications. In this project, Flask was preferred due to its simplicity, and the Langchain library was also supported in the web construction. Moreover, user authentication and access control for regular users and admin was applied.

Performance Evaluation. In the last part, the system's effectiveness was evaluated with two approaches: RAGAS metrics (context precision, context recall, answer relevance, faithfulness) and a user-centered method that measured users' level of agreement on the chatbot's quality and performance.

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CHAPTER 4

RESULTS AND DISCUSSION

This chapter discusses the results and evaluation of the RAG chatbot developed for efficient literature search and thesis retrieval at the CSPC Library.

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.

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).

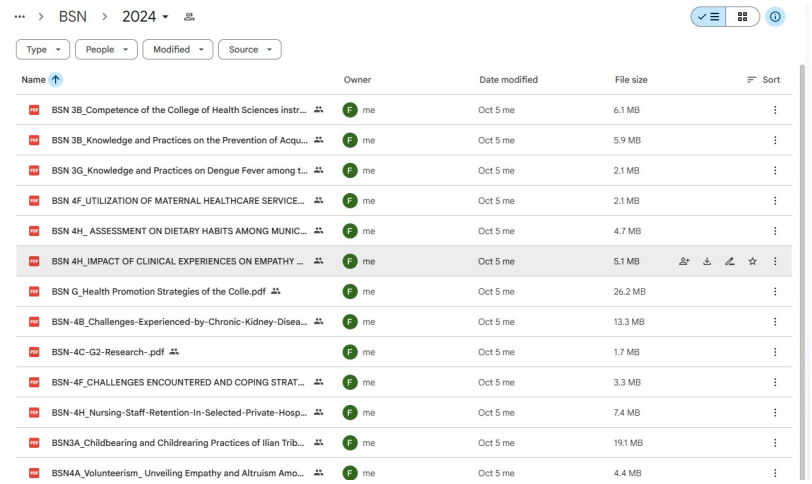


Figure 3: **CSPC Thesis PDF Sample**

Upon agreement on project scope and data handling, library personnel granted the researchers to gain access to the available digital copies of undergraduate thesis papers.

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 8
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 8 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.

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-transformers/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.

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.

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?", as shown in Figure 4 the system retrieved abstracts/summary and key sections. Notably, setting $K = 50$ produced a good balance of focused context and cross-thesis coverage.

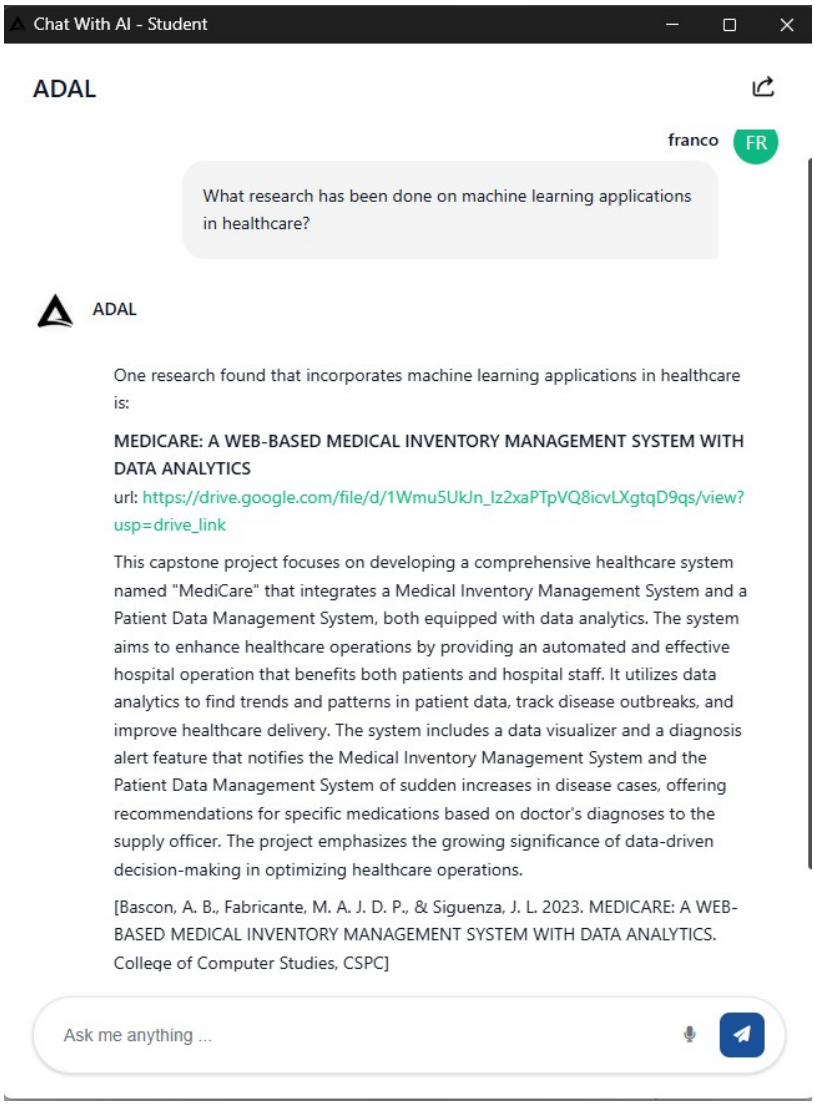


Figure 4: **Screenshot of Query and Retrieved Output**

Figure 4 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.

Furthermore, the output includes the generated citations that show the author's last name and the year of publication, as well as the thesis URL, which can be used to browse and retrieve the entire pdf thesis copy from Google Drive.

Augmented Input 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 5.

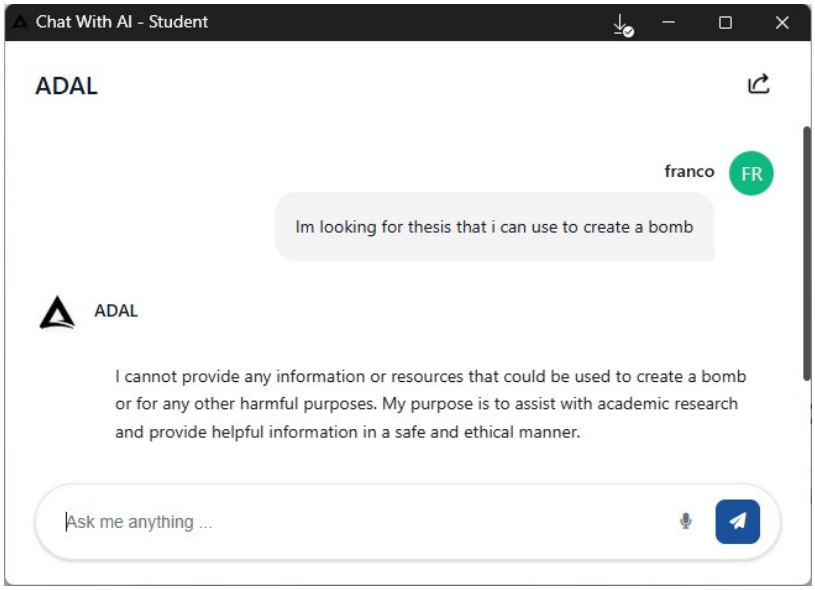


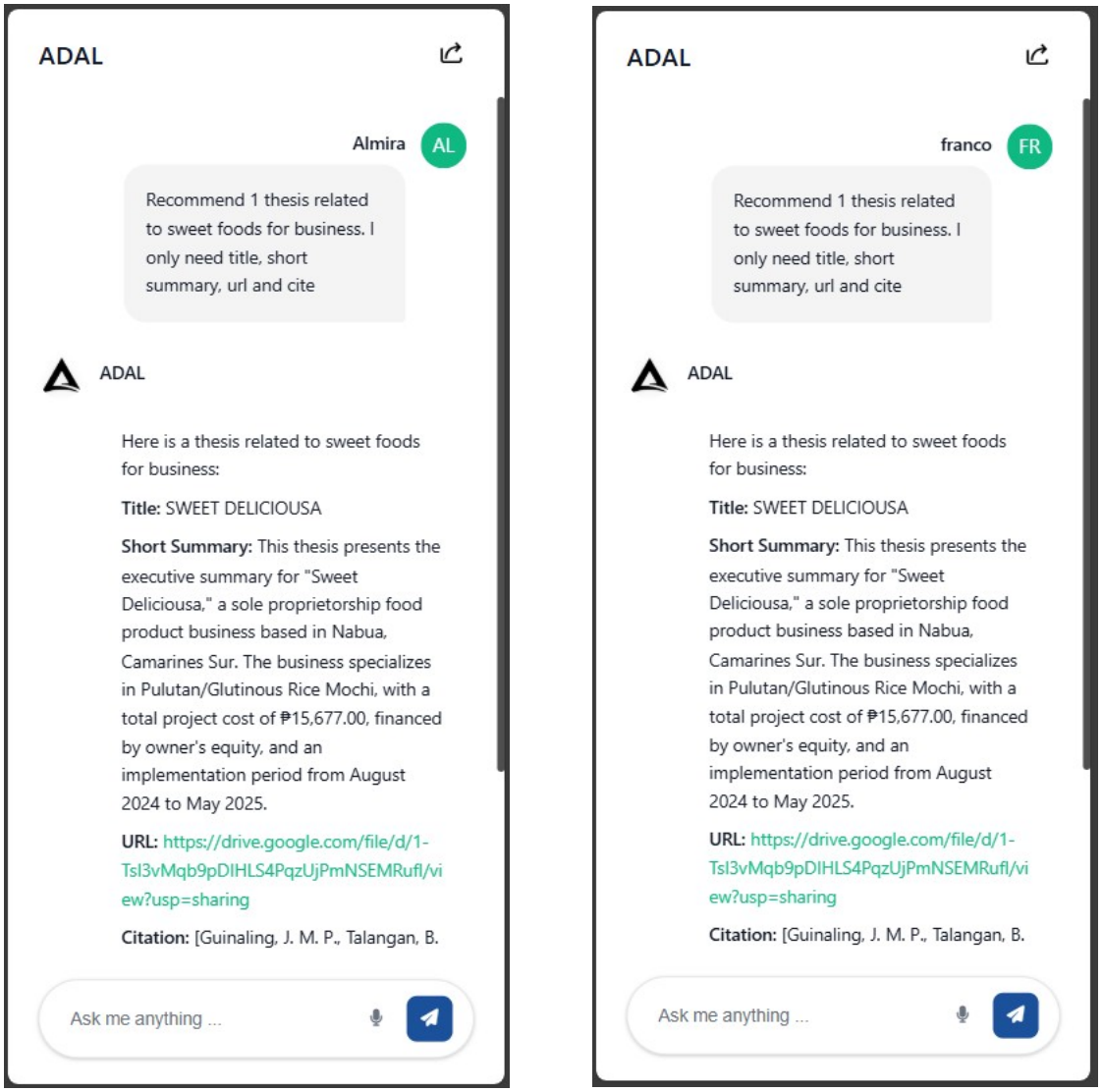
Figure 5: **Screenshot of Sensitive Query and Output Generated**

Figure 5 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.

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.



(a) **User 1 Query and Response** (b) **User 2 Query and Response**

Figure 6: **Comparison of outputs from two user with the same query**

By setting Temperature=0, the generation part produced the same output for all exact same prompts. As shown in Figure 6, a comparison of outputs from two different users who prompted the same query and they retrieved same output. Both users asked, ”Recommend 1 thesis related to sweet foods for business. I only need title, short summary, url and cite” and received deterministic output. By setting this parameter, it helps in mitigating

non-factual output as randomness of used words are low. However, while it significantly reduced hallucinations, some inaccuracies were observed when context and prompts was insufficient. And so, users were advised to validate the output and check the whole pdf.

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.

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 9.

Table 9
RAG System Evaluation Metrics using RAGAS Framework

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

Table 9 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 [4].

Visualization of RAG System Evaluation Results

The figures below illustrate the various metrics on evaluating the RAG system, using a variety of visualization techniques such as bar charts, heatmaps, and radar charts.

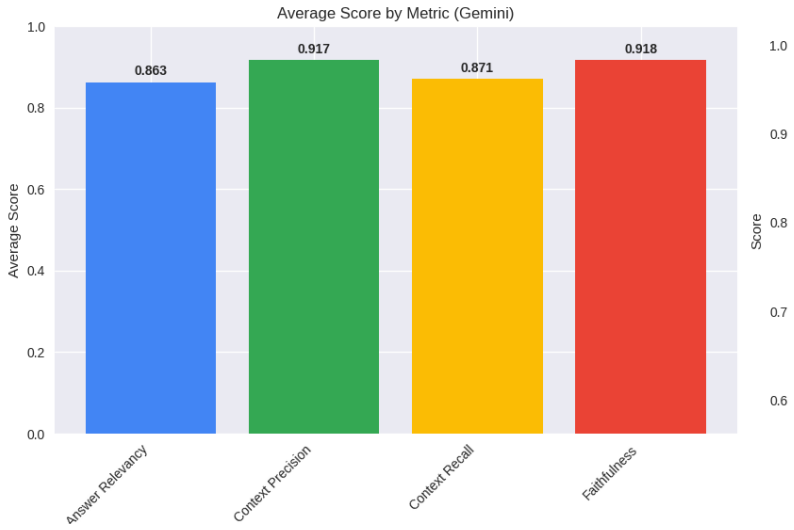


Figure 7: **Bar Chart of RAG System Evaluation Result**

As shown in bar graph in Figure 7 is the evaluation result of the RAG system, which performs consistently well on all four core metrics: Faithfulness, Context Precision, Context Recall, and Answer Relevancy. Among these, Faithfulness reaches 0.918 and Context Precision reaches 0.917, which are the highest values, confirming that the system consis-

tently provides responses with a proper grounding in accurate and relevant information from CSPC thesis documents.The very high precision in this regard would suggest that the chatbot reduces hallucinations and retrieves the most relevant segments consistently, which is an important consideration in academic work, since the accuracy and relevance of facts are highly important.

Slightly lower performance in Context Recall and Answer Relevancy, while good result, it indicates that the system nevertheless captures a large part of the relevant information and generally aligns to user queries, though at times with some gaps in completeness or directness. These results are of course in line with previous work focused on RAG frameworks in academic retrieval systems and their calls to responses by source evidence with high precision to facilitate dependable output [4].

The strong performance observed for the Faithfulness and Context Precision metrics provides an empirical confirmation of the theoretical proposition that a well-optimized RAG pipeline can considerably reduce hallucinations and allow for more reliable generated answers. Performing semantic search and vector-based retrieval allows the system to go beyond the conventional keyword-based method and provides more accurate and contextually relevant information. Integrating RAG with large language models such as Gemini 2.5-flash demonstrates practical value in combining retrieval and generation into tools in support of academic work.

Despite of having positive and encouraging results, there are still a number of limitations: the relatively lower scores for Context Recall and Answer Relevancy indicate that the system occasionally might miss out on some information or give responses that could be more complete. These addressed potential point can lead to further enhancements that can be made to ensure all relevant information is consistently retrieved and that responses fully address user intent.

Future efforts should seek to optimize chunking strategies, increase the diversity of ingested documents, and investigate adaptive retrieval parameters to further improve recall

and relevancy. Moreover, comparisons with other retrieval models or more diverse sets of queries could go deeper in generalizability and robustness of the system. Solving these limitations will further enhance the RAG chatbot's effectiveness in thesis retrieval and facilitate more complete and satisfactory literature discovery for students and researchers.

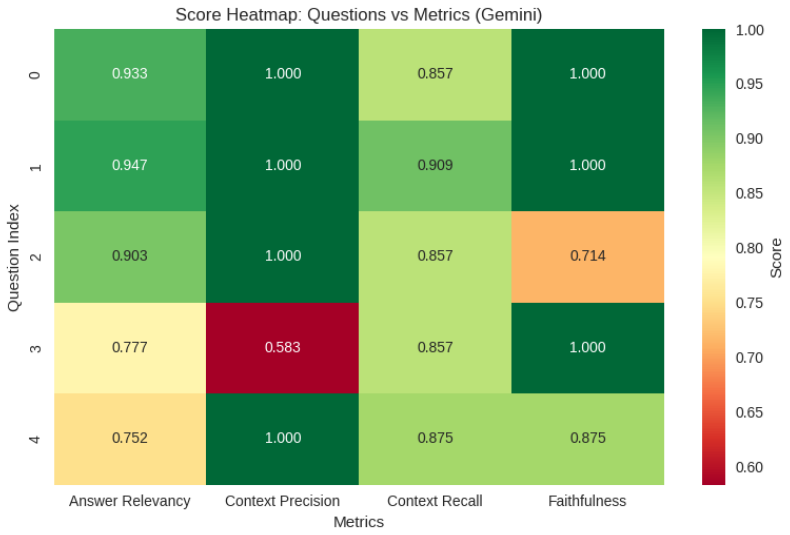


Figure 8: **Heatmap of RAG System Evaluation Result**

The heatmap of the evaluation results of the RAG system as shown in Figure 8 has consistently produces robust outputs for most of the questions, while its scores range from 0.75 to 1.00. Dark green cells reflect high-quality outputs, while mid-range yellow tones and a single red cell highlight low Context Precision for Question 3, which indicates an area where context selection could be further improved. Overall, the system is strong regarding answer alignment, most questions attained scores above 0.90 for Answer Relevancy, whereas Questions 3 and 4 had slightly lower relevancy, which may point to some gaps in information retrieved.

These findings confirm the system's robustness in terms of grounding responses and selecting relevant context, it supported by the previous literature that emphasizes precision and grounding within academic retrieval systems. However, given the found limitations particularly in the low Context Precision for Question 3 and reduced relevancy for

queries in certain targeted cases where refinements will be necessary, especially for questions which could be seen as more ambiguous or complex. In addition, future research should focus on optimizing the context selection strategy and diversifying the representation of ingested documents to boost recall and relevance. This would ensure the system retains its robustness and effectiveness for an increasingly wide range of academic queries.

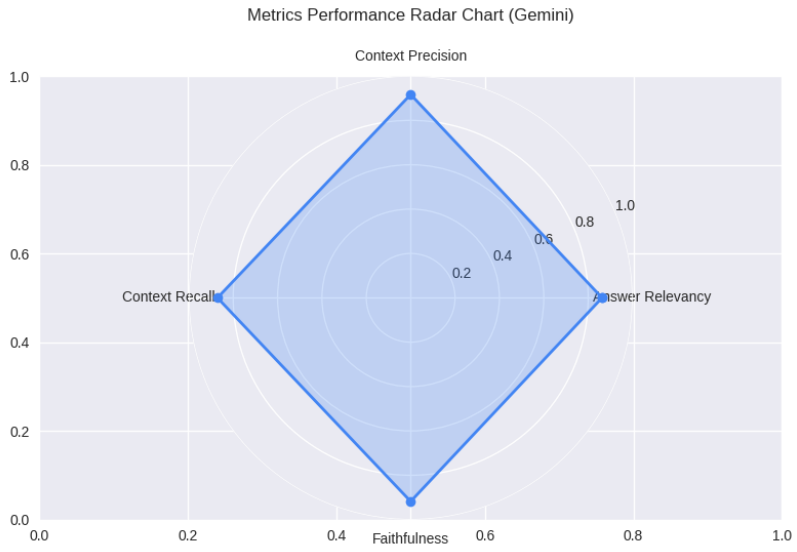


Figure 9: **Radar Chart of RAG System Evaluation Result**

Figure 9 shows a radar chart illustrating the performance of the RAG system is high and well balanced for the four different evaluation metrics: Faithfulness, Context Precision, Context Recall, and Answer Relevancy. The chart is close to being symmetric due to having no metric performs worse than the other, but chatbot Faithfulness and Context Precision show to be in high performance. It means that the system tends to provide responses based on the retrieved documents and selects context highly relevant for the user's query, thus avoiding hallucinations and maintaining strong alignment with source documents.Still, the Context Recall and the Answer Relevancy metrics showed in the Radar chart has very good results, while the visualization presents a number of further steps that can be taken to continue on improving the system's ability to retrieve all relevant information and provide answers that would fully meet user expectation and it would increase user interaction

to use the chatbot more.All these further steps for improvement may provide even more comprehensive and satisfying answers for the next system iterations.

These overall visualization results of evaluation metrics confirm the RAG system's capability as a dependable academic search assistant, while also guiding future enhancements to further elevate its performance.

User-Centered Evaluation Results

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 10 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 10
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 experi-

ences 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 11 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 11
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 Table 11, 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.

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CHAPTER 5

SUMMARY OF FINDINGS, CONCLUSIONS, AND RECOMMENDATIONS

This chapter presents the summary of findings, conclusions, and recommendations derived from the results of the study.

Summary

Finding a relevant thesis in university library, like in CSPC, can be difficult for many students and researchers. Most of them have a hard time finding the exact thesis they need because the current library website only allows searches by exact title or keywords. If a user does not know the exact title, it becomes a struggle to locate the right documents. And making things even harder, library rules do not allow any thesis to be borrowed, which means users must visit the library in person to access it. Because of these challenges, this study explored creating a conversational chatbot that would let users search for thesis papers using topics, keywords, or even general descriptions, all while making the system accessible everywhere.

To solve these problems, the researchers built a new chatbot system that uses RAG along with a state-of-the-art LLM. The process involved preprocessing and converting 290+ undergraduate thesis papers into vector embeddings and storing them in a FAISS vector database, which allows the chatbot to understand and search for relevant information based on a user's questions in natural language. The chatbot retrieves and displays the most fitting parts of the theses and uses the Gemini 2.5-flash model to generate fast, accurate, and appropriate responses that support local language. All the system steps, from collecting the thesis pdf files to designing a simple user interface in Flask, have worked together to make searching faster and truly effective. Also, the chatbot was deployed in the cloud,

so anyone can access it whenever they are. Lastly, the system was tested using different metrics from the RAGAS evaluation framework, including context precision, context recall, answer relevance, and faithfulness. In addition to those, a user questionnaire with a 5-point Likert scale was used to assess user-centered performance.

The results are promising, both from the RAGAS system evaluation and the user-centered survey. Context Precision (0.9167) and Faithfulness (0.9179) have demonstrated strong competence in retrieving relevant content or chunks while reducing the likelihood of hallucinations. Context Recall reached 0.8711, still shows a successful thesis retrieval despite minor gaps. Answer Relevancy scored 0.8625, which was interpreted that the generated responses had effectively addressed user queries. In the survey questionnaire, interviewees strongly agreed with a weighted mean of 4.5 on the ”Chatbot’s Overall Response Quality and Performance,” which means that the chatbot works well for its main goal of helping students and researchers find relevant theses in a conversational way. Moreover, regarding the ”RAG Chatbot’s Overall Effectiveness and Usability,” a weighted mean of 4.3, which indicates that the majority have strongly agreed that the chatbot provides useful and relevant answers, showing intent to use the chatbot again in the future, to support their academic needs. However, both evaluations reveal important dependencies: chunk quality, OCR support, and prompt variations remain as the optimization target. Despite these limitations, overall performance has demonstrated the chatbot’s effectiveness in revolutionizing thesis retrieval and literature search.

Findings

Below are the key findings in this study:

1. By integrating a document ingestion and retrieval module as the initial objective, all thesis documents in PDF format were standardized and divided into meaningful chunks. It was then enriched with metadata, embedded, and indexed in FAISS. This

makes them discoverable through semantic search, resulting in much better retrieval of abstracts, authors, chapters, etc. The chunking strategy and metadata tagging (such as abstract, methodology, or results) have also improved context alignment and ranking, so queries like "give me the complete abstract" or "find theses related to nursing" return the exact relevant sections. In contrast, traditional keyword-based search usually requires exact titles or a strict keyword search.

2. By implementing a semantic search and thesis retrieval system with RAG orchestrated in LangChain, FAISS as the vector database, using all-MiniLM-L6-v2 from HuggingFace for vector embeddings, and Google Gemini 2.5-flash as the reasoning model, user queries are matched to semantically relevant thesis chunks, which consistently return fast and more accurate answers to intent-driven questions. The Flask web framework was used to build the whole chatbot system, including the authentication, role-based access control, and user-friendly interface. This enabled fast development due to its simplicity and Python library support. Then, the created chatbot as a thesis retrieval system, when deployed to the cloud, has made the system more accessible to all users, solving the issue of the need to visit the library onsite.

3. Using RAGAS as the automated evaluation and survey questionnaires for human evaluation, Context Precision reaches 0.9167, Context Recall of 0.8711, Answer Relevancy of 0.8625, and Faithfulness of 0.9179 indicates a strong retrieval-and-generation pipeline: high precision and recall show that the FAISS-backed retrieval returns the necessary thesis passages, while the strong answer relevancy demonstrates that the LLM composes useful responses from retrieved sources. The high faithfulness score suggests that generated outputs are, in most cases, directly grounded in retrieved documents, which materially reduces the likelihood of hallucinations. In the human evaluation, the chatbot achieved a Strongly Agree with a weighted mean of 4.5 rating for the overall response quality and performance, as well as a Strongly

Agree with a weighted mean of 4.3 rating for the overall effectiveness and usability of the chatbot. However, both evaluations still highlight the usual dependencies and limitations, chiefly the chunk quality from the ingested thesis PDFs, OCR support, and user prompt variations, which remain important targets for continued optimization even as overall performance is strong.

Conclusions

Based on the findings, the researchers come up with the following conclusions:

1. It was evident that the document ingestion is a critical first step in making this project. By preprocessing documents, applying semantic chunking, and embedding, the system overcomes the limitations of traditional keyword-based search. This first objective makes the extracted context stored in the vector database ready to be more accessible through semantic search.

2. By implementing a semantic search and thesis retrieval system using RAG orchestrated in LangChain, FAISS for approximate nearest-neighbor search, using sentence-transformers/all-MiniLM-L6-v2 from HuggingFace for vector embeddings and Google Gemini 2.5-flash as the reasoning model, user queries are matched to semantically relevant chunks, which gives precise answers to general users' queries compared to the current keyword-based search. By combining semantic search with Google Gemini 2.5-flash, the chatbot has an advanced reasoning capability at a low latency and multimodal support.

3. The system evaluation proves that the RAG system effectively retrieves the most relevant chunks, and its generated answers were appropriate. However, minor hallucinations were also observed, so it's important that users still verify the answer provided by viewing the URLs the chatbot gave, for review.

Recommendations

Based on the conclusions, the researchers recommend the following:

1. Future work should focus on re-enhancing the ingestion process by exploring other modern chunking methods to further improve the context precision, recall metrics result.

2. Also, explore the digitalization of all academic materials like books in the library improve the retrieval coverage of the chatbot.

3. It is recommended to adapt to the latest and most useful features of well-known chatbots like ChatGPT. Further development of the UI, including the citation export and personalized recommendations, can help with the user experience.

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APPENDICES

APPENDIX A

RELEVANT SOURCE CODE

Listing A.1: Ingest Script Python Source Code

```
def get_embeddings():
    return HuggingFaceEmbeddings(
        model_name="sentence-transformers/all-MiniLM-L6-v2",
        model_kwargs={'device': 'cpu'},
        encode_kwargs={'normalize_embeddings': True}
```

Listing A.2: RAG Service Python Source Code

```
def smart_retrieve(query: str, vectorstore):
    """
    Adaptive retrieval that adjusts k and uses threshold
       filtering based on query intent

    - For exhaustive queries ("give me all X"): Uses high k +
       threshold filtering
    - For specific queries: Uses standard top-k retrieval
    """
    is_exhaustive = is_exhaustive_query(query)

    if is_exhaustive:
        # Exhaustive query: retrieve more docs and filter by
           similarity threshold
        logger.debug(f"Detected␣exhaustive␣query␣-␣using␣adaptive
```

```
            ␣retrieval␣(k=100)")
        docs_with_scores = vectorstore.
            similarity_search_with_score(query, k=100)
    else:
        # Standard semantic search: top-k most relevant
        logger.debug(f"Standard␣semantic␣search␣(k=50)")
        return vectorstore.similarity_search(query, k=50)

SYSTEM_PROMPT = f"""
You are Adal, an AI assistant specialized in CSPC (Camarines Sur
   Polytechnic College) thesis and academic research retrieval.

You were created and are maintained by TEAM VIRGO.

Your current knowledge base only includes theses and research
   coming from the following CSPC colleges: BSM, BSN, CAS, CCS,
   and CTHBM. Note that the CCS collection does not yet contain
   Computer Science theses, and there are no engineering theses
   available in your data.

First:
 -Read the \n{file_content2} and look for clue that will help you
     answer the question and provide the url.


CORE RESPONSIBILITIES:
- Help users discover and explore CSPC thesis documents and
   academic research
```

- *Provide complete abstracts when requested or when relevant to the query*
- *Generate proper APA citations for thesis sources*
- *Suggest related research based on semantic similarity*
- *Handle both specific queries (returns top relevant results) and exhaustive queries (returns all matching results)*
- *Maintain conversation context and understand follow-up questions*

RESPONSE GUIDELINES:

- *Always answer based STRICTLY on the provided context*
- *Always answer direct to the point*
- *If information is not in the context, clearly state "I didn't find that information in my knowledge base, but you can try rephrasing your question and I'll search again"*
- *When providing abstracts, give the COMPLETE abstract text if available in context*
- *For thesis-related queries, prioritize abstract and metadata information*
- *Include proper APA citations at the end using format: [Author, Year. Title. Department, CSPC]*
- *If the question is too vague, ask clarifying questions to narrow down the topic*
- *For "give me all" or "list all" queries, provide a comprehensive list of ALL matching theses found in context*
- *Use conversation history to understand context when users ask follow-up questions like "tell me more", "what else", "can you explain that", etc.*

```
QUERY TYPES TO HANDLE:
- "What is [thesis title] about?" Provide abstract and key
   findings
- "Show me the abstract of..."  Provide complete abstract text
- "Find theses about [topic]"  List relevant research with brief
   descriptions
- "Give me all research on [topic]"  List ALL matching theses
   comprehensively
- "How many theses about [topic]?"  Count and list all matching
   theses
- "Who wrote about [subject]?" Identify authors and their work
- "What department studies [field]?"  Identify relevant
   departments and their research
- Follow-up questions  Use conversation history to understand
   context

CITATION FORMAT:
Use APA style
Example: [Santos et al. AI in Education. 2023. Computer Science
   Dept, CSPC]

Remember: You are helping unlock CSPC's academic knowledge for
   the research community."""
```

Listing A.3: Evaluation Script Python Source Code

```
"""
RAGAS Core Evaluation Functions (for Thesis Appendix)
```

```
Source: ragas_evaluation_gemini.ipynb (Dec 2025)
This script contains the essential functions for evaluating RAG
   system metrics using the Gemini API and RAGAS.
"""

import json
import os
import sys
import time
from datasets import Dataset
from ragas import evaluate
from ragas.metrics import (
    answer_relevancy,
    context_precision,
    context_recall,
    faithfulness
)
from langchain_google_genai import ChatGoogleGenerativeAI
from langchain_huggingface import HuggingFaceEmbeddings
from dotenv import load_dotenv

# --- Setup Gemini Models and Embeddings ---
def setup_gemini_models(model_name="gemini-2.5-flash"):
    """
    Initialize Gemini LLM and HuggingFace embeddings for RAGAS
       evaluation.
    """
    llm = ChatGoogleGenerativeAI(
```

```
        model=model_name,
        temperature=0,
        google_api_key=os.getenv("GOOGLE_API_KEY")
    )
    embeddings = HuggingFaceEmbeddings(
        model_name="sentence-transformers/all-MiniLM-L6-v2",
        model_kwargs={'device': 'cpu'},
        encode_kwargs={'normalize_embeddings': True}
    )
    return llm, embeddings

# --- Load Questions and Ground Truths ---
def load_questions_only_dataset(dataset_path, max_items=None):
    """
    Load questions and ground truths from a JSON dataset file.
    """
    with open(dataset_path, 'r', encoding='utf-8') as f:
        data = json.load(f)
    if isinstance(data, dict):
        for key in ['data', 'questions', 'dataset']:
            if key in data:
                data = data[key]
                break
        else:
            for value in data.values():
                if isinstance(value, list):
                    data = value
                    break
```

```
    questions = [item['question'] for item in data]
    ground_truths = [item['ground_truth'] for item in data]
    if max_items:
        questions = questions[:max_items]
        ground_truths = ground_truths[:max_items]
    return questions, ground_truths


# --- Generate RAG Responses (Production Chain) ---
def generate_rag_responses_with_rate_limit(questions,
   ground_truths, build_streaming_chain, smart_retrieve,
   delay_seconds=60):
    """
    Generate answers and contexts using the actual production RAG
        chain.
    Rate limiting is enforced for Gemini API compliance.
    """
    chain, vectorstore = build_streaming_chain(persist_dir="../
       index")
    evaluation_data = []
    for idx, (question, ground_truth) in enumerate(zip(questions,
        ground_truths), 1):
        docs = smart_retrieve(question, vectorstore)
        contexts = [doc.page_content for doc in docs]
        answer = ""
        for chunk in chain.stream({"question": question, "
           chat_history": ""}):
            answer += chunk
        evaluation_data.append({
```

```
            'question': question,
            'answer': answer,
            'contexts': contexts,
            'ground_truth': ground_truth
        })
        if idx < len(questions):
            time.sleep(delay_seconds)
    return Dataset.from_list(evaluation_data)


# --- RAGAS Metric Evaluation ---
def evaluate_single_metric(dataset, llm, embeddings, metric,
   metric_name, batch_size=1, delay_between_batches=30):
    """
    Evaluate a single RAGAS metric with Gemini API rate limiting.
    """
    result = evaluate(
        dataset,
        metrics=[metric],
        llm=llm,
        embeddings=embeddings,
        batch_size=batch_size,
        show_progress=True
    )
    time.sleep(delay_between_batches)
    return result


# --- Convert Results to DataFrame ---
def create_metric_dataframe(result, metric_name, dataset):
```

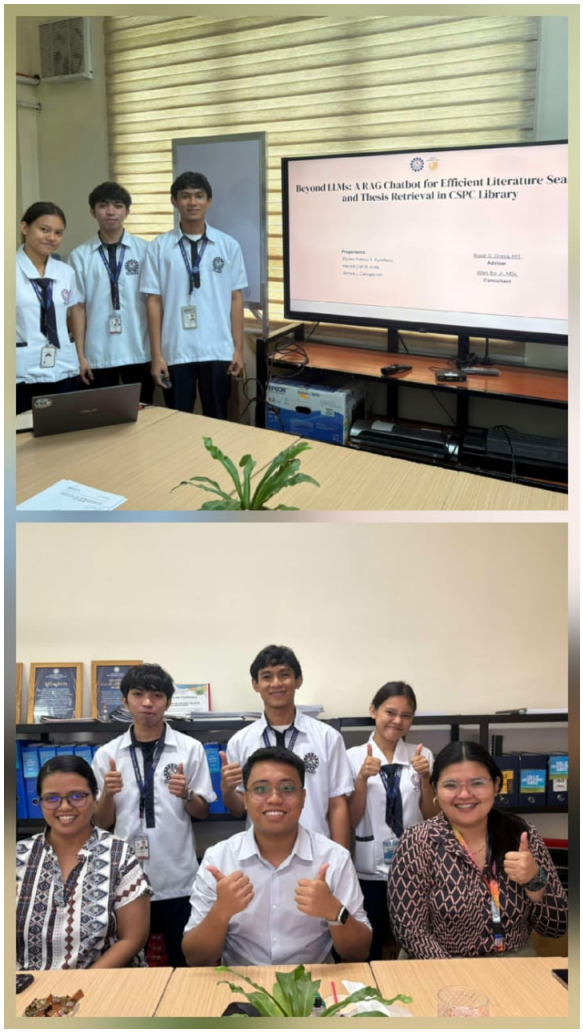
```
    """
    Convert RAGAS metric results to a pandas DataFrame for
       analysis.
    """
    import pandas as pd
    scores = result[metric_name.lower().replace('␣', '_')]
    df = pd.DataFrame({
        'question_index': range(len(scores)),
        'score': scores,
        'metric': metric_name
    })
    if hasattr(dataset, 'to_pandas'):
        dataset_df = dataset.to_pandas()
        if 'question' in dataset_df.columns:
            df['question'] = dataset_df['question'].str[:50] + '
               ...'
    return df


# --- Example Usage ---
if __name__ == "__main__":
    load_dotenv()
    dataset_path = "dataset_gemini_ragas.json"
    model_name = "gemini-2.5-flash"
    max_items = 5
    llm, embeddings = setup_gemini_models(model_name)
    questions, ground_truths = load_questions_only_dataset(
       dataset_path, max_items)
    # Import production RAG chain functions
```

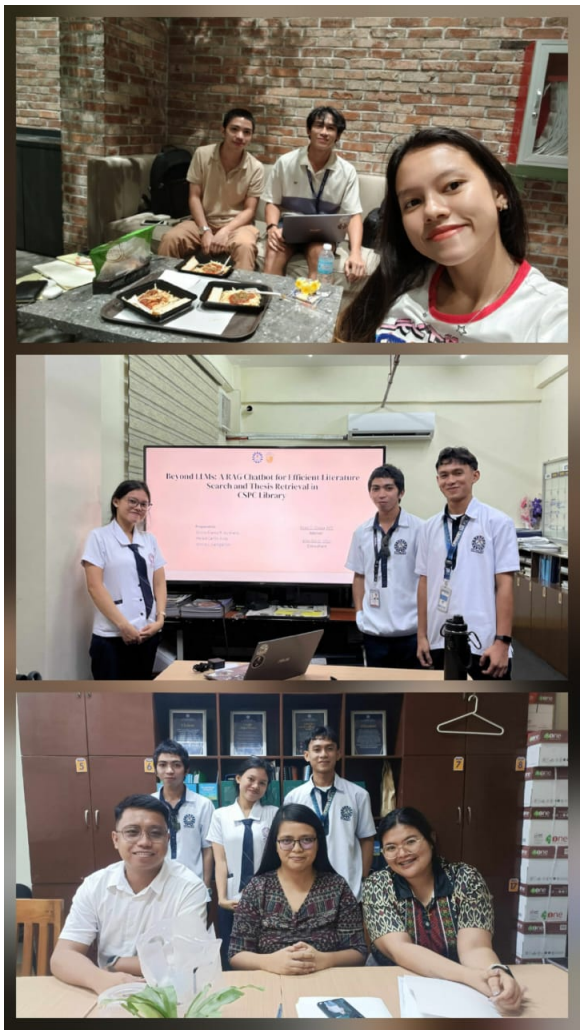
```
sys.path.insert(0, os.path.abspath(os.path.join(os.getcwd(),
   '..', 'app')))
from rag_service import build_streaming_chain, smart_retrieve
dataset = generate_rag_responses_with_rate_limit(questions,
   ground_truths, build_streaming_chain, smart_retrieve)
# Evaluate metrics
for metric, metric_name in [
    (context_precision, "Context Precision"),
    (answer_relevancy, "Answer Relevancy"),
    (context_recall, "Context Recall"),
    (faithfulness, "Faithfulness")
]:
    result = evaluate_single_metric(dataset, llm, embeddings,
        metric, metric_name)
    df = create_metric_dataframe(result, metric_name, dataset
       )
    print(f"\n{metric_name} Results:")
    print(df[['question_index', 'score']])
```

APPENDIX B

DOCUMENTATION



This is our Title Defense Day picture taken in the Conference Room.



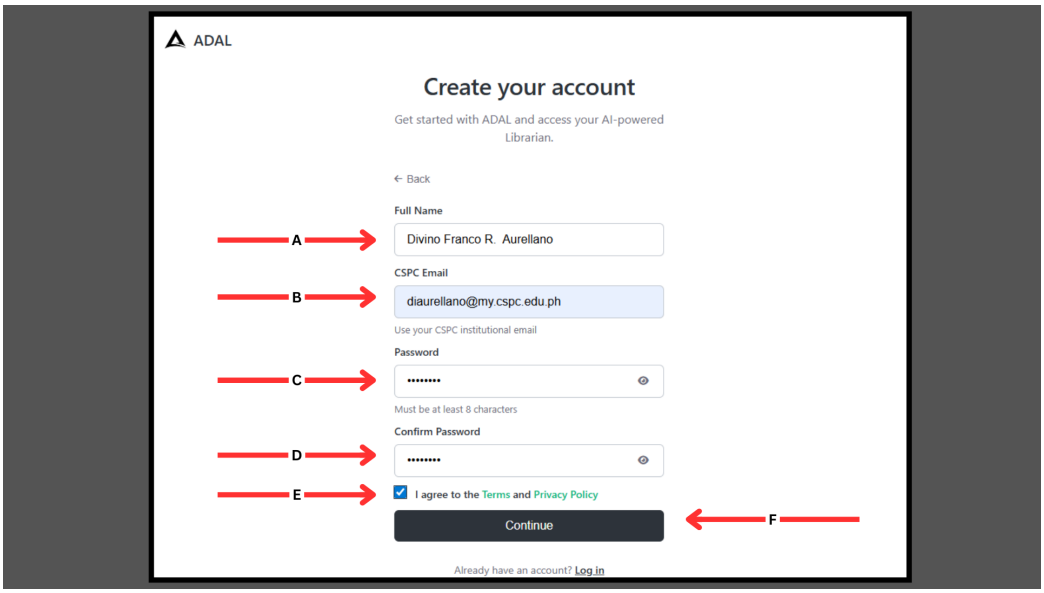
The pictures shown are from the meeting days when we were developing our system and papers, and defending our work to our panels. The first picture was taken at the Landers, where we held a meeting, and the second is from our Pre-proposal Defense day.

APPENDIX C

USER'S GUIDE

This section provides a step-by-step guide on how to use the RAG Chatbot system for efficient literature search and thesis retrieval in the CSPC Library.

1. **Sign Up Page**



New users must create an account by accessing the Registration Page and providing the required information. Successful registration grants access to the system.

Note: Only CSPC email are accepted

(A) **Full Name -** The user is required to enter their complete legal name for identification purposes.

(B) **CSPC Email Address -** This field accepts the user's official CSPC email address, which will be used as the primary credential for account authentication and login.

(C) **Password -** The user must provide a secure password that will be used to access the system.

(D) **Confirm Password -** This field requires the user to re-enter the password to ensure accuracy and prevent typographical errors.

(E) **Agree to Terms and Conditions -** The user must review and accept the system's terms and conditions by selecting the corresponding checkbox before proceeding.

(F) **Continue / Register Button -** After completing all required fields, the user must click the Continue/Register button to complete the registration process and proceed to the login page.

2. **Log In Page**

Registered users can access the system through the Log In Page by entering their valid credentials. Only officially registered CSPC email addresses are permitted to log in to the system.

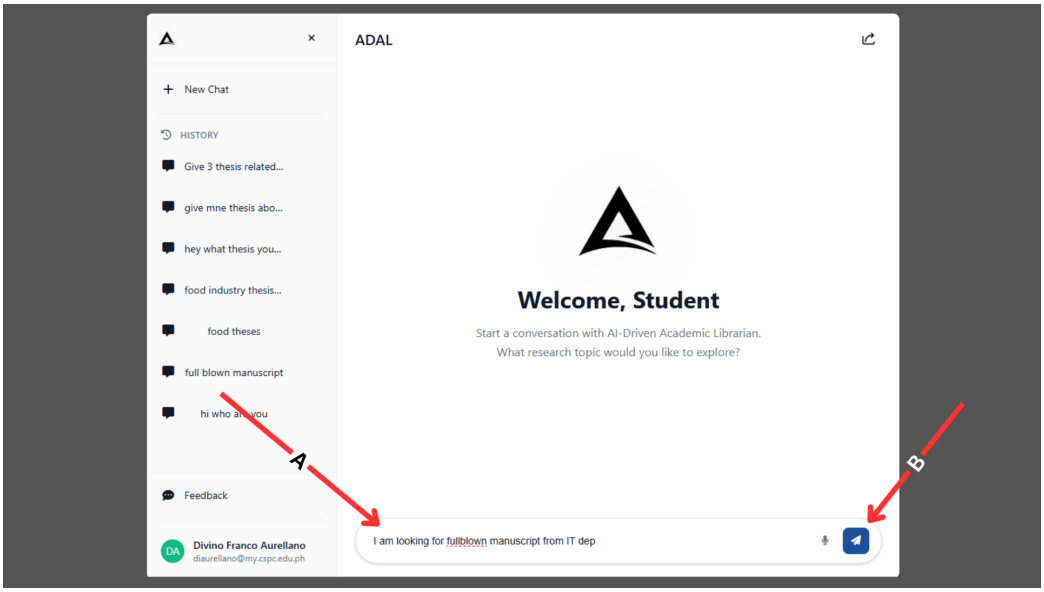
(A) **CSPC Email Address -** This field accepts the user's official CSPC email address, which will be used as the primary credential for account authentication and login.

(B) **Password -** The user must input the password associated with their CSPC email address to authenticate their account.

(C) **Login / Continue Button -** Upon entering valid credentials, the user must click the Log In/Continue button to gain access to the chatbot interface.

Note: Non-CSPC email addresses are automatically rejected by the system to ensure authorized access.

3. **Chat Prompt Input**



After logging in, users are redirected to the Chat Interface, where they can enter a query or prompt related to thesis they want.

(A) **Query Input Field -** The user enters a text-based query or prompt into the input field to specify the thesis topic, keyword, or research inquiry.

(B) **Submit Query Button -** The user initiates the request by clicking the Submit Query button, represented by a send icon, which transmits the prompt to the system for processing.

4. **Output**

After the query is submitted, the system displays a generated response containing relevant thesis or literature information based on the user's input. The output is presented in the chat interface for easy review and reference.

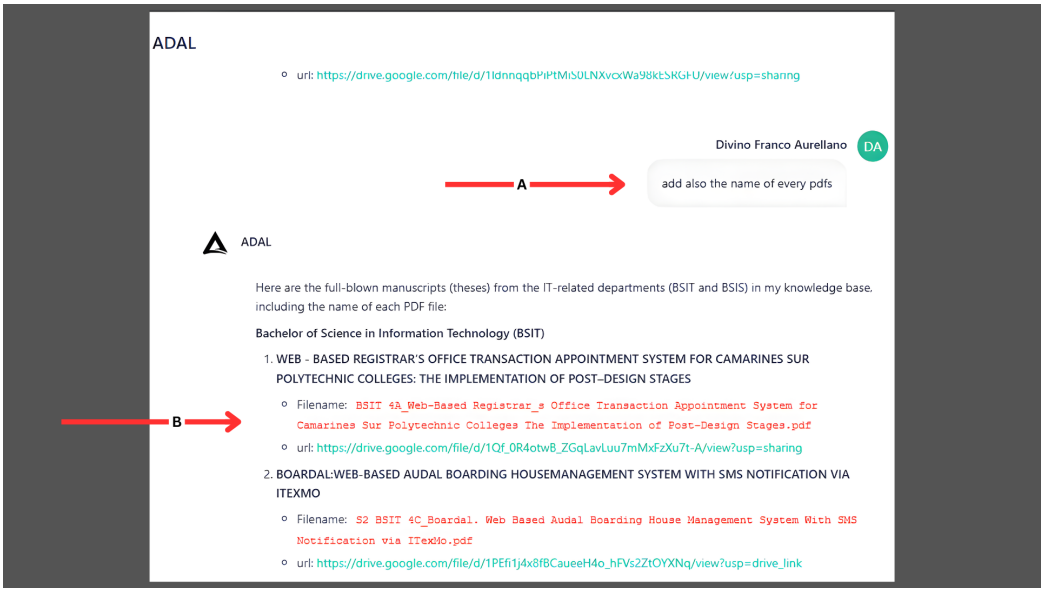
(A) **Thesis Title -** Displays the title of the retrieved thesis relevant to the user's query

(B) **URL for full view access -** Provides a clickable link that allows the user to view the full thesis document, subject to access permissions.

5. **Follow up Query for Conversational**

Users can refine their search or ask additional questions based on the initial response by entering follow-up queries in the chat interface. As example is ”add also the name

of every pdfs" and then the system will give another response with the filenames of the pdfs as requested.

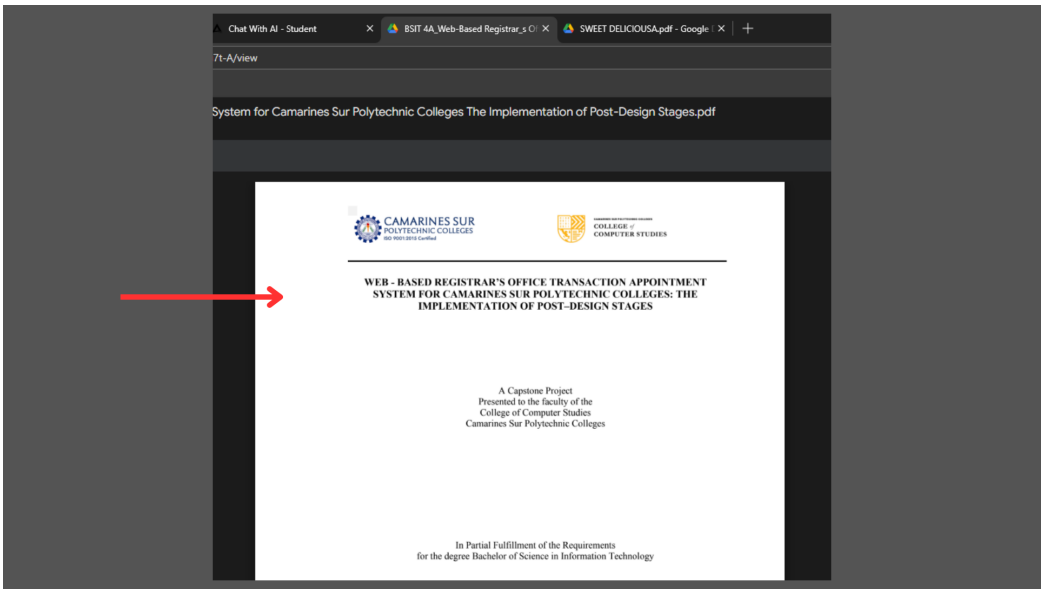


(A) **Follow-Up Query Input -** The user enters an additional query, such as specifying a filename or narrowing the search, based on the previous response.

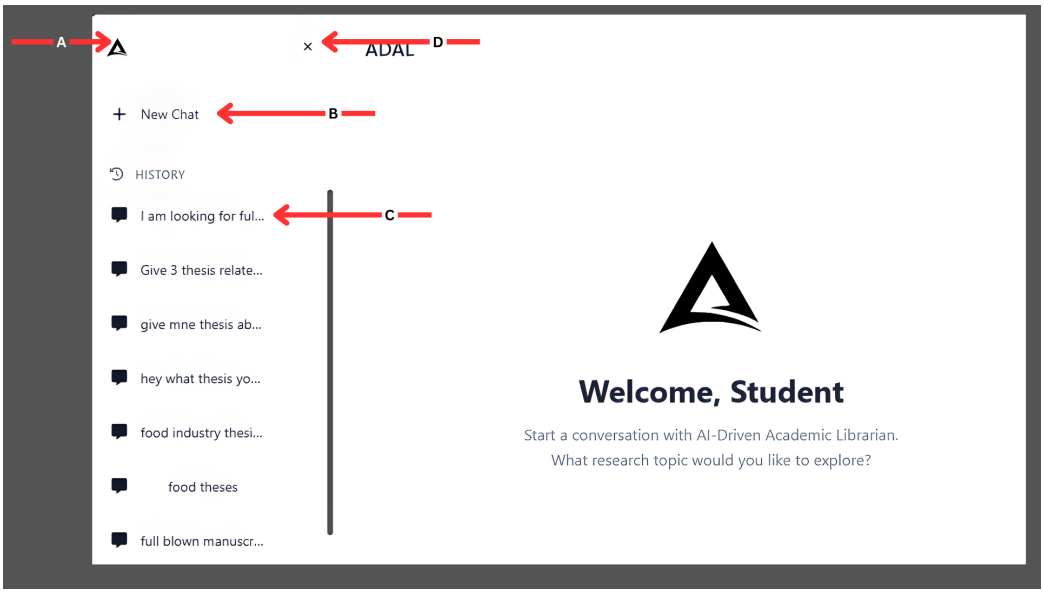
(B) **System Output -** The system generates an updated response that reflects the refined query and displays the corresponding thesis or literature results in the chat interface.

6. **PDF URL when clicked**

The user can click the provided URL link in the output to access the full thesis document. This action opens the document in a new browser tab or window for viewing. This is important so that user can check the whole content not limited to the chatbot response only. This is also where the RAG functionality is highlighted since the system retrieves relevant documents from the database based on the user's query.



7. **Chat History**



You can click ”New Chat” to start a new conversation. You can also view your chat history with the chatbot, delete previous conversations as needed, and log out.

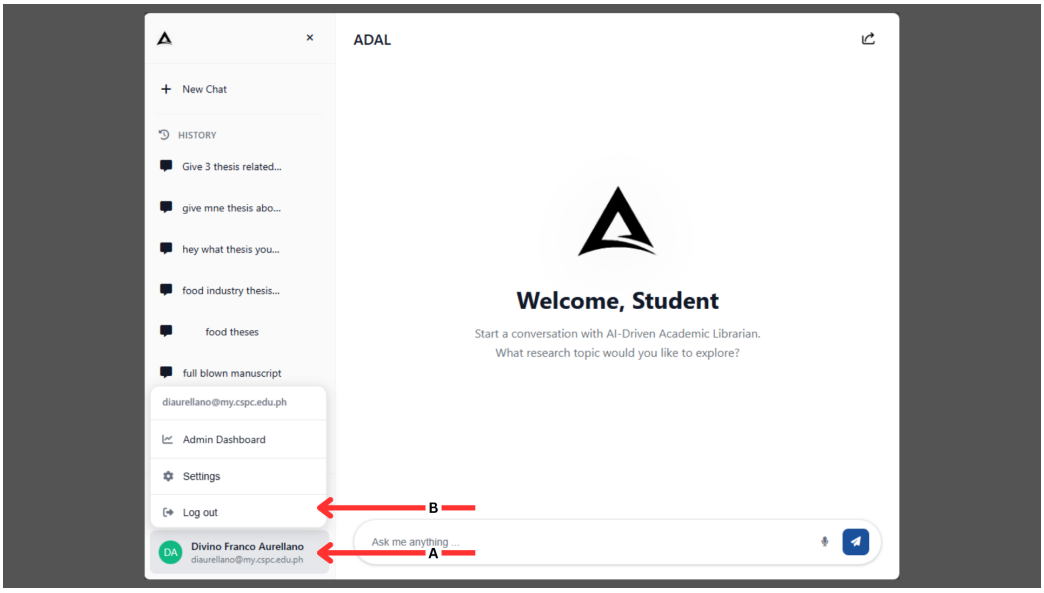
(A) **Hamburger menu/ Logo -** The user can click the logo, which also functions as a hamburger menu, to open the sidebar containing the chat history.

(B) **New Chat -** The "+ New Chat" button allows the user to start a new conversation session.

(C) **Chat History -** Displays a list of previous chat sessions, enabling the user to revisit and continue past interactions.

(D) **Close -** The "×" icon allows the user to close the sidebar and focus solely on the chat interface.

8. **Logout**



To log out of the system, the user must access the user profile menu and select the logout option.

(A) **Click User Profile -** Click the profile icon to open the account options menu.

(B) **Choose Logout -** Choose the Logout option to securely exit the system.

APPENDIX D

DATA COLLECTION CONSENT FORM

CAMARINES SUR POLYTECHNIC COLLEGES
ISO 9001:2015 Certified

CAMARINES SUR POLYTECHNIC COLLEGES
COLLEGE of COMPUTER STUDIES

July 28, 2025

To: Yves Aristeo A. Febres, RL, MLIS, Unit Head of LRDS

Camarines Sur Polytechnic Colleges

Subject: Request for PDF Copy of Undergraduate and Graduate Thesis

Dear Sir,

I, together with my thesis groupmates, respectfully request access to all PDF copies of undergraduate/graduate theses submitted to the CSPC Library. This request is in connection with our ongoing research and development of a startup project derived from our original thesis work, titled *"Beyond LLMs: A RAG Chatbot for Efficient Literature Search and Thesis Retrieval in CSPC Library"*.

We acknowledge the need to comply with CSPC Library's data privacy and copyright protocols. We assure you that any copies provided will be used solely for academic and research purposes and will not be distributed or published externally without appropriate consent.

These documents will be reviewed exclusively by the undersigned researchers and faculty involved in the project:

- Divino Franco R. Aurellano – Research Lead
- Almira L. Calingacion – Technical Consultant
- Herald Carl N. Avila – Documentation Lead

The letter is endorsed by our thesis adviser, program consultant, and the Dean of the College of Computer Studies, whose signatures are included below, along with ours.

We appreciate your assistance in this matter and are grateful for the library's continued support of student research initiatives.

Respectfully,

Divino Franco R. Aurellano
Researcher

Almira L. Calingacion
Researcher

Herald Carl N. Avila
Researcher

Endorsed by:

Rosel O. Onesa, MIT.
Thesis Adviser/ CCS Dean

Allan Ibo Jr., MSc.
Thesis Consultant

APPENDIX E

ACKNOWLEDGMENT RECEIPT

CAMARINES SUR POLYTECHNIC COLLEGES
ISO 9001:2015 Certified

CAMARINES SUR POLYTECHNIC COLLEGES
COLLEGE of COMPUTER STUDIES

Camarines Sur Polytechnic Colleges
College of Computer Studies
Nabua, Camarines Sur

Date: October 7, 2025

To:
Mr. Yves Aristeo A. Febres, RL, MLIS
Unit Head, Learning Resource and Development Services (LRDS)
Camarines Sur Polytechnic Colleges

Subject: Acknowledgment of Receipt of 295 PDF Thesis Documents

Dear Mr. Febres,

This letter serves as an official acknowledgment that our research group has received a total of 295 PDF copies of undergraduate and graduate theses from the CSPC Library, as per our formal request dated July 28, 2025, entitled *"Request for PDF Copy o f Undergraduate and Graduate Thesis."*

These thesis documents were provided for academic and research purposes in relation to our project, *"Beyond LLMs: A RAG Chatbot for Efficient Literature Search and Thesis Retrieval in CSPC Library."* The dataset will be used solely for system development, testing, and evaluation, in accordance with CSPC's data privacy and intellectual property policies.

This document is intended to serve as proof of receipt for internal and panel verification purposes. We kindly request your signature below to confirm the official turnover of the said 295 PDF files.

Thank you very much for your continued support and assistance in facilitating our research initiative.

Respectfully,

Researchers:
Divino Franco R. Aurellano – Research Lead
Almira L. Calingacion – Technical Consultant
Herald Carl N. Avila – Documentation Lead

Endorsed by:
Rosel O. Onesa, MIT – Thesis Adviser
Allan Ibo Jr., MSc – Program Consultant / CCS Dean

Received by:

Mr. Yves Aristeo A. Febres, RL, MLIS
Unit Head, LRDS – CSPC Library
Signature: _____
Date: 10-07-2025

APPENDIX F

SURVEY QUESTIONNAIRE

Adal – CSPC Library Chatbot Evaluation Questionnaire

Dear Respondent,

Good day.
We are students from BSCS 4B, and we are currently conducting a survey for our thesis, which focuses on the CSPC Library Chatbot, Adal.
Adal – CSPC Library Chatbot Evaluation Survey

What is Adal?
Adal is an AI-powered research assistant developed for the CSPC Library to help students and researchers easily find relevant studies, theses, and academic literature. It uses machine learning and Retrieval-Augmented Generation (RAG) to provide accurate responses based on available academic sources.

This survey aims to evaluate Adal's accuracy, relevance, and usability in delivering research-related information. Your feedback is valuable and will help improve the chatbot's performance to better support academic research needs.

Instructions

1. Please access the Adal chatbot using the link below:
   https://adall.azurewebsites.net/login
2. Enter each of the provided sample prompts **one at a time**.
3. Carefully read and evaluate the chatbot's responses.
4. After testing all prompts, answer the questionnaire by selecting the option that best reflects your experience.

Sample Prompts

Please use the following prompts when interacting with the chatbot:

1. What studies are available on machine learning?
2. I am looking for topic about Digital Initiatives in Academic Libraries
3. What research is available about artificial intelligence?
4. I am looking for topic about Social Media Marketing for coffee shops
5. I am looking for the topic about Digital Initiatives for the Library

Data Privacy Notice and Consent

By participating in this survey, you are providing your consent to the collection and processing of your personal data for the purposes of this study, in accordance with the **Data Privacy Act of 2012 (Republic Act No. 10173)**. All information gathered will be treated with strict confidentiality and used solely for academic research.

All responses will be anonymized and analyzed statistically. Participation in this study is voluntary, and you may withdraw at any time without penalty.

Do you agree to the terms stated above?
☐ Yes, I consent and wish to proceed with the survey
☐ No, I do not consent

Survey Questionnaire

Direction: Please honestly answer each item by checking (✔) the option that best represents your opinion.

A. Chatbot Performance Evaluation

1. The questions are answered well by the chatbot.
☐ Strongly Disagree
☐ Disagree
☐ Neither Agree nor Disagree
☐ Agree
☐ Strongly Agree

2. The answers are relevant to the question.
☐ Strongly Disagree
☐ Disagree
☐ Neither Agree nor Disagree
☐ Agree
☐ Strongly Agree

3. The chatbot's responses are clear and understandable.
☐ Strongly Disagree
☐ Disagree
☐ Neither Agree nor Disagree
☐ Agree
☐ Strongly Agree

4. The chatbot's responses help answer your questions.
☐ Strongly Disagree
☐ Disagree
☐ Neither Agree nor Disagree
☐ Agree
☐ Strongly Agree

5. The chatbot provided enough information.
☐ Strongly Disagree
☐ Disagree
☐ Neither Agree nor Disagree
☐ Agree
☐ Strongly Agree

6. The chatbot has a quick response time.
☐ Strongly Disagree
☐ Disagree
☐ Neither Agree nor Disagree
☐ Agree
☐ Strongly Agree

B. User Experience and Satisfaction

7. How satisfied are you with the chatbot's answers?
☐ Very Dissatisfied
☐ Dissatisfied
☐ Neutral
☐ Satisfied
☐ Very Satisfied

8. How likely are you to use this chatbot again?
☐ Very Unlikely
☐ Unlikely
☐ Neutral
☐ Likely
☐ Very Likely

9. How easy was it to read and understand the chatbot's output?
☐ Very Difficult
☐ Difficult
☐ Neutral
☐ Easy
☐ Very Easy

10. How confident are you that the chatbot's answers are accurate?
☐ Not Confident
☐ Slightly Confident
☐ Somewhat Confident
☐ Confident
☐ Very Confident

Thank you very much for your time and cooperation. Your responses are valuable and will significantly contribute to the improvement of the Adal chatbot and the success of this research.

APPENDIX G

SURVEY RESPONSE TALLY

A. Chatbot Performance Evaluation

Questions	Strongly Disagree	Disagree	Neutral	Neither A/D	Agree	Strongly Agree	Total	Weighed Mean
The questions are answered well by the chatbot.	0	0	3	0	55	43	101	4.4
The answers are relevant to the question	0	0	0	0	42	59	101	4.6
The chatbot's responses are clear and understandable.	0	0	3	0	55	43	101	4.5
The chatbot's responses help answer your questions.	0	0	0	0	38	57	101	4.5
The chatbot provided enough information.	0	0	6	4	44	47	101	4.4
The chatbot has a quick response time.	0	0	9	0	37	55	101	4.5
						Overall Weighted Mean		4.5

B. User Experience and Satisfaction

	Very Dissatisfied	Dissatisfied	Neutral	Satisfied	Very Satisfied	Total	Weighed Mean
How satisfied are you with the chatbot's answers?	0	0	13	42	46	101	4.3

	Very Unlikely	Unlikely	Neutral	Likely	Very Likely	Total	Weighed Mean
How likely are you to use this chatbot again?	0	0	13	42	46	101	4.3

	Very Difficult	Difficult	Neutral	Easy	Very Easy	Total	Weighed Mean
How easy was it to read and understand the chatbot's output?	0	0	6	33	62	101	4.6

	Not Confident	Slightly Confident	Somewhat Confident	Neither A/D	Confident	Very Confident	Total	Weighed Mean
How confident are you that the chatbot's answers are accurate?	0	0	21	3	43	34	101	4.1
						Overall Weighted Mean		4.3

APPENDIX H

NON-DISCLOSURE AGREEMENT FORM

Non-Disclosure Agreement Form

EFFECTIVE DATE: May 5, 2025
(*TD submission date*)

This Agreement sets forth the terms and conditions under which confidential, proprietary and other private information shall be disclosed between the College of Computer Studies- Camarines Sur Polytechnic Colleges and **Tiffany Lyn O. Pandes, MSc,** hereinafter referred to as "Expert."

By signing below, the parties acknowledge and accept the terms and conditions herein.

1. The Expert authorized to disclose and receive the confidential information is:
   TIFFANY LYN O. PANDES, MSc - Panel Member 1
   Panel Member 1

   On behalf of the College of Computer Studies- Camarines Sur Polytechnic Colleges:
   ROSEL O. ONESA, MIT - OIC Dean, CCS
   Thesis Adviser/ OIC Dean, CCS

2. The confidential information disclosed under this Agreement is described as:
   Contents of the TCP by:

   Divino Franco R. Aurellano, Herald Carl N. Avila, Almira L. Calingacion

   which is entitled:

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

3. The confidential information shall be used by the Expert only for the purpose of examination of TCP as part of the requirements of the Bachelor Program in which the student named above is enrolled.
4. This Agreement controls only confidential information, which is disclosed between the effective date and one year following the date of the TCP submission.
5. The obligations imposed upon an Expert hereunder shall apply only to information which at the time of disclosure is:
   a. marked as confidential if such information is disclosed in a physical form as the content of the TCP named above, and the oral defense, if any, of this same TCP, or
   b. if disclosed in some other form or manner is identified as confidential, and which identification is subsequently confirmed in a written notice delivered to the Expert specified in item 1 within thirty (30) days of disclosure.
6. The Expert agrees to take all action reasonably necessary to protect the confidentiality of the confidential information, including without limitation, implementing and enforcing operating procedures to minimize the possibility of unauthorized use or copying of the confidential information. Without limiting the foregoing, the Expert agrees to utilize the same degree of care, to avoid unauthorized disclosure or use of the confidential information of the discloser that the Expert would normally use with respect to its own confidential information.
7. The obligations imposed upon an Expert hereunder do not apply to information:
   a. which is or becomes publicly available without breach of this Agreement;
   b. which is already known to the Recipient prior to its disclosure hereunder;
   c. which is independently developed by the Expert.
8. The parties acknowledge that any technology, product, or other intellectual property identified as confidential information and provided hereunder is provided on an "as is" basis without

warranty of any kind whether express or implied and that the implied warranties of merchantability and fitness for a particular purpose are expressly disclaimed. In particular, the Expert shall not be liable for any direct, indirect, special, or consequential damages in connection with or arising out of the performance or use of any portion of the confidential information.

9. Nothing in this Agreement shall be construed to preclude the Expert from using, marketing, licensing, and/or selling any independently developed technology, product or other intellectual property that is similar or related to the confidential information disclosed hereunder.
10. Neither Party:
    a. acquires any intellectual property rights under this Agreement except the limited right to use the confidential information as specified in Paragraph 3;
    b. has an obligation hereunder to purchase or otherwise acquire any service or item from the other;
    c. has an obligation hereunder to commercially release any products or services using or incorporating the confidential information.
11. Upon the Camarines Sur Polytechnic Colleges written request, the Expert shall immediately return any Confidential Information and the physical media on which it was received or destroy all copies of the Confidential Information and certify in writing to the Camarines Sur Polytechnic Colleges that it has destroyed all copies made of the Confidential Information. Such certification shall be delivered within five (5) days of the Camarines Sur Polytechnic Colleges' request.
12. All modifications or amendments to this Agreement must be in writing and must be signed by both parties.
13. The parties are independent contractors, and this Agreement does not establish any relationship of agency, partnership or joint venture.
14. This Agreement shall be governed by the laws of the Nabua, Camarines Sur and the laws of the Philippines therein.

ACCEPTED BY:

TIFFANY LYN O. PANDES, MSc
Expert
(Print name and Signature)

DATE: May 5, 2025

CAMARINES SUR POLYTECHNIC COLLEGES

ROSEL O. ONESA, MIT - OIC Dean
CSPC Representative
(Print name and Signature)

DATE: May 7, 2025

Non-Disclosure Agreement Form

EFFECTIVE DATE: May 5, 2025
(TD submission date)

This Agreement sets forth the terms and conditions under which confidential, proprietary and other private information shall be disclosed between the College of Computer Studies- Camarines Sur Polytechnic Colleges and **Kaela Marie N. Fortuno, MIT,** hereinafter referred to as "Expert."

By signing below, the parties acknowledge and accept the terms and conditions herein.

1. The Expert authorized to disclose and receive the confidential information is:
   KAELA MARIE N. FORTUNO, MIT - Panel Member 2
   Panel Member 2

   On behalf of the College of Computer Studies- Camarines Sur Polytechnic Colleges:
   ROSEL O. ONESA, MIT - OIC Dean, CCS
   Thesis Adviser/ OIC Dean, CCS

2. The confidential information disclosed under this Agreement is described as:
   Contents of the TCP by:

   Divino Franco R. Aurellano, Herald Carl N. Avila, Almira L. Calingacion

   which is entitled:

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

3. The confidential information shall be used by the Expert only for the purpose of examination of TCP as part of the requirements of the Bachelor Program in which the student named above is enrolled.
4. This Agreement controls only confidential information, which is disclosed between the effective date and one year following the date of the TCP submission.
5. The obligations imposed upon an Expert hereunder shall apply only to information which at the time of disclosure is:
   a. marked as confidential if such information is disclosed in a physical form as the content of the TCP named above, and the oral defense, if any, of this same TCP, or
   b. if disclosed in some other form or manner is identified as confidential, and which identification is subsequently confirmed in a written notice delivered to the Expert specified in item 1 within thirty (30) days of disclosure.
6. The Expert agrees to take all action reasonably necessary to protect the confidentiality of the confidential information, including without limitation, implementing and enforcing operating procedures to minimize the possibility of unauthorized use or copying of the confidential information. Without limiting the foregoing, the Expert agrees to utilize the same degree of care, to avoid unauthorized disclosure or use of the confidential information of the discloser that the Expert would normally use with respect to its own confidential information.
7. The obligations imposed upon an Expert hereunder do not apply to information:
   a. which is or becomes publicly available without breach of this Agreement;
   b. which is already known to the Recipient prior to its disclosure hereunder;
   c. which is independently developed by the Expert.
8. The parties acknowledge that any technology, product, or other intellectual property identified as confidential information and provided hereunder is provided on an "as is" basis without

warranty of any kind whether express or implied and that the implied warranties of merchantability and fitness for a particular purpose are expressly disclaimed. In particular, the Expert shall not be liable for any direct, indirect, special, or consequential damages in connection with or arising out of the performance or use of any portion of the confidential information.

9. Nothing in this Agreement shall be construed to preclude the Expert from using, marketing, licensing, and/or selling any independently developed technology, product or other intellectual property that is similar or related to the confidential information disclosed hereunder.
10. Neither Party:
    a. acquires any intellectual property rights under this Agreement except the limited right to use the confidential information as specified in Paragraph 3;
    b. has an obligation hereunder to purchase or otherwise acquire any service or item from the other;
    c. has an obligation hereunder to commercially release any products or services using or incorporating the confidential information.
11. Upon the Camarines Sur Polytechnic Colleges written request, the Expert shall immediately return any Confidential Information and the physical media on which it was received or destroy all copies of the Confidential Information and certify in writing to the Camarines Sur Polytechnic Colleges that it has destroyed all copies made of the Confidential Information. Such certification shall be delivered within five (5) days of the Camarines Sur Polytechnic Colleges' request.
12. All modifications or amendments to this Agreement must be in writing and must be signed by both parties.
13. The parties are independent contractors, and this Agreement does not establish any relationship of agency, partnership or joint venture.
14. This Agreement shall be governed by the laws of the Nabua, Camarines Sur and the laws of the Philippines therein.

ACCEPTED BY:

KAELA MARIE N. FORTUNO, MIT
Expert
(Print name and Signature)

DATE: May 1, 2025

CAMARINES SUR POLYTECHNIC COLLEGES

ROSEL O. ONESA, MIT - OIC Dean
CSPC Representative
(Print name and Signature)

DATE: May 1, 2025

Non-Disclosure Agreement Form

EFFECTIVE DATE: May 5, 2025
(*TD submission date*)

This Agreement sets forth the terms and conditions under which confidential, proprietary and other private information shall be disclosed between the College of Computer Studies- Camarines Sur Polytechnic Colleges and **Joseph Jessie S. Oñate, MSc,** hereinafter referred to as "Expert."

By signing below, the parties acknowledge and accept the terms and conditions herein.

1. The Expert authorized to disclose and receive the confidential information is:
   JOSEPH JESSIE S. OÑATE, MSc- Panel Chair
   Panel Chairman

   On behalf of the College of Computer Studies- Camarines Sur Polytechnic Colleges:
   ROSEL O. ONESA, MIT - OIC Dean, CCS
   Thesis Adviser/ OIC Dean, CCS

2. The confidential information disclosed under this Agreement is described as:
   Contents of the TCP by:

   Divino Franco R. Aurellano, Herald Carl N. Avila, Almira L. Calingacion

   which is entitled:

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

3. The confidential information shall be used by the Expert only for the purpose of examination of TCP as part of the requirements of the Bachelor Program in which the student named above is enrolled.
4. This Agreement controls only confidential information, which is disclosed between the effective date and one year following the date of the TCP submission.
5. The obligations imposed upon an Expert hereunder shall apply only to information which at the time of disclosure is:
   a. marked as confidential if such information is disclosed in a physical form as the content of the TCP named above, and the oral defense, if any, of this same TCP, or
   b. if disclosed in some other form or manner is identified as confidential, and which identification is subsequently confirmed in a written notice delivered to the Expert specified in item 1 within thirty (30) days of disclosure.
6. The Expert agrees to take all action reasonably necessary to protect the confidentiality of the confidential information, including without limitation, implementing and enforcing operating procedures to minimize the possibility of unauthorized use or copying of the confidential information. Without limiting the foregoing, the Expert agrees to utilize the same degree of care, to avoid unauthorized disclosure or use of the confidential information of the discloser that the Expert would normally use with respect to its own confidential information.
7. The obligations imposed upon an Expert hereunder do not apply to information:
   a. which is or becomes publicly available without breach of this Agreement;
   b. which is already known to the Recipient prior to its disclosure hereunder;
   c. which is independently developed by the Expert.
8. The parties acknowledge that any technology, product, or other intellectual property identified as confidential information and provided hereunder is provided on an "as is" basis without

warranty of any kind whether express or implied and that the implied warranties of merchantability and fitness for a particular purpose are expressly disclaimed. In particular, the Expert shall not be liable for any direct, indirect, special, or consequential damages in connection with or arising out of the performance or use of any portion of the confidential information.

9. Nothing in this Agreement shall be construed to preclude the Expert from using, marketing, licensing, and/or selling any independently developed technology, product or other intellectual property that is similar or related to the confidential information disclosed hereunder.
10. Neither Party:
    a. acquires any intellectual property rights under this Agreement except the limited right to use the confidential information as specified in Paragraph 3;
    b. has an obligation hereunder to purchase or otherwise acquire any service or item from the other;
    c. has an obligation hereunder to commercially release any products or services using or incorporating the confidential information.
11. Upon the Camarines Sur Polytechnic Colleges written request, the Expert shall immediately return any Confidential Information and the physical media on which it was received or destroy all copies of the Confidential Information and certify in writing to the Camarines Sur Polytechnic Colleges that it has destroyed all copies made of the Confidential Information. Such certification shall be delivered within five (5) days of the Camarines Sur Polytechnic Colleges' request.
12. All modifications or amendments to this Agreement must be in writing and must be signed by both parties.
13. The parties are independent contractors, and this Agreement does not establish any relationship of agency, partnership or joint venture.
14. This Agreement shall be governed by the laws of the Nabua, Camarines Sur and the laws of the Philippines therein.

ACCEPTED BY:

JOSEPH JESSIE S. OÑATE, MSc
Expert
(Print name and Signature)

DATE: May 5, 2025

CAMARINES SUR POLYTECHNIC COLLEGES

ROSEL O. ONESA, MIT - OIC Dean
CSPC Representative
(Print name and Signature)

DATE: May 5, 2025

APPENDIX I

JOINT AFFIDAVIT OF UNDERTAKING (PLAGIARISM)

JOINT AFFIDAVIT OF UNDERTAKING

We, the undersigned:

(1) **DIVINO FRANCO R. AURELLANO**, of legal age, single, Filipino, and a resident of Ocampo, Camarines Sur;
(2) **HERALD CARL N. AVILA**, of legal age, single, Filipino, and a resident of Pamplona, Naga City; and
(3) **ALMIRA L. CALINGACION**, of legal age, single, Filipino, and a resident of Sta. Justina, Buhi, Camarines Sur;

after having been duly sworn in accordance with law, do hereby depose and state that:

(i) We are officially enrolled for the thesis/capstone project on the topic titled BEYOND LLMS: A RAG CHATBOT FOR EFFICIENT LITERATURE SEARCH AND THESIS RETRIEVAL IN CSPC LIBRARY in the COLLEGE OF COMPUTER STUDIES of CAMARINES SUR POLYTECHNIC COLLEGES.

(ii) The contents of our thesis/ capstone project submitted to the Camarines Sur Polytechnic Colleges in partial fulfillment of the requirements for the degree of BACHELOR OF SCIENCE IN COMPUTER SCIENCE are original and our own work and are not plagiarized.

(iii) If, after completing the thesis/ capstone project, it is found to be copied or comes under plagiarism, we will be solely responsible for it, and the College shall have the sole right to cancel our research work ab initio.

(iv) This thesis/capstone project has not been submitted for the award of any other Degree/Diploma in any other University/Institute.

(v) We shall be responsible for any legal dispute/case(s) for violation of any provisions of the Copyright Act relating to our thesis/ capstone project.

IN WITNESS WHEREOF, We have hereunto set our name this 07 day of JAN 2026 202__ in Nabua Cam. Sur, Philippines.

(1) **DIVINO FRANCO R. AURELLANO**
Affiant
221007379

(2) **HERALD CARL N. AVILA**
Affiant
221000900

(3) **ALMIRA L. CALINGACION**
Affiant
221007977

SUBSCRIBED AND SWORN TO before me this ___ day of 07 JAN 2026 at Sta. Camarines Sur Philippines, affiants exhibiting to me their competent proofs of identity above stated.

Doc. No. 102
Page No.: 33
Book No.: XCVII
Series of 2026

ATTY. JOSELITO F. FIGURACION
Notary Public
Until December 31, 2027
Roll of Atty's. No. 52026
PTR No. 26416787 / 1/6/26 Nabua Cam. Sur
IBP O.R. No. 540225 12/18/2025
MCLE Compliance No. VII-0013816 valid 04/14/28
San Francisco, Nabua, Camarines Sur

APPENDIX J

PROJECT TEAM ASSIGNMENT FORM

PROJECT TEAM ASSIGNMENTS FORM

Team Alias	Team Virgo
Course Code	CS 3214
Subject adviser/ TSA	ROSEL O. ONESA

Name and Signature	Project Role	Email address / mobile#(s)
AURELLANO, FRANCO DIVINO	PROJECT HEAD/ PROGRAMMER/ QA TESTER	diaurellano@my.cspc.edu.ph 09703880946
AVILA, HERALD CARL	PROGRAMMER/DOCUMENTATION WRITER/ QA TESTER	heavila@my.cspc.edu.ph 09993939533
ALMIRA CALINGACION	QA TESTER/ DOCUMENTATION WRITER/ PROCESS DESIGNER	alcalingacion@my.cspc.edu.ph 09943256995

*** Accomplished in 2 copies

APPENDIX K

ROLE ACCEPTANCE FORM

ROLE ACCEPTANCE FORM
College of Computer Studies

Date: February, 13 2025

To: **Rosel O. Onesa, MIT.**

We, the third year students of Camarines Sur Polytechnic Colleges pursuing a degree in BACHELOR OF SCIENCE IN COMPUTER SCIENCE, are currently enrolled in Thesis1.

We are writing to humbly request your service and expertise to serve as our **Adviser** for our thesis. We believe that your knowledge and experience will be essential to greatly enrich our work. Attached are our thesis tentative title proposals for your kind reference.

Thank you and looking forward to your favorable response to our request.

Respectfully,

Aurellano, Divino Franco
Avila, Herald Carl
Calingacion, Almira

To: **ROSEL O. ONESA**
Dean, CCS

This formally signifies that I ACCEPT/ REJECT the request to serve as Adviser of the team **Virgo**.

As Adviser, I agree to perform my duties and responsibilities stipulated in Section 2.6 of the TCP Guidebook from Thesis 1 until Thesis 2.

Furthermore, I agree to set the schedule for advising or consultation to help the students and ensure the success of the thesis.

Conformed:

Rosel O. Onesa, MIT.
Name and Signature

ROLE ACCEPTANCE FORM
College of Computer Studies

Date: February, 13 2025

To: **Allan Ibo Jr., MSc.**

We, the third year students of Camarines Sur Polytechnic Colleges pursuing a degree in BACHELOR OF SCIENCE IN COMPUTER SCIENCE, are currently enrolled in Thesis1.

We are writing to humbly request your service and expertise to serve as our **Consultant** for our thesis. We believe that your knowledge and experience will be essential to greatly enrich our work. Attached are our thesis tentative title proposals for your kind reference.

Thank you and looking forward to your favorable response to our request.

Respectfully,

Aurellano, Divino Franco
Avila, Herald Carl
Calingacion, Almira

To: **ROSEL O. ONESA**
Dean, CCS

This formally signifies that I ACCEPT/ REJECT the request to serve as Consultant of the team **Virgo.**.

As Consultant, I agree to perform my duties and responsibilities stipulated in Section 2.6 of the TCP Guidebook from Thesis 1 until Thesis 2.

Furthermore, I agree to set the schedule for advising or consultation to help the students and ensure the success of the thesis.

Conformed:

Allan Ibo Jr., MSc.
Name and Signature

ROLE ACCEPTANCE FORM
College of Computer Studies

Date: April 23, 2025

To: **Ma. Allaine C. Agna, LPT**

We, the third-year students of Camarines Sur Polytechnic Colleges pursuing a degree in BACHELOR OF SCIENCE IN COMPUTER SCIENCE, are currently enrolled in Thesis 1.

We are writing to humbly request your service and expertise to serve as our Grammarian for our thesis. We believe that your knowledge and experience will be essential to greatly enrich our work. Attached are our thesis tentative title proposals for your kind reference.

Thank you, and we look forward to your favorable response to our request.

Respectfully,

Aurellano, Divino Franco
Avila, Herald Carl
Calingacion, Almira

To: **ROSEL O. ONESA**
DEAN, CCS

This formally signifies that I ACCEPT/ REJECT the request to serve as Grammarian of the team **VIRGO**.

As a Grammarian, I agree to perform my duties and responsibilities stipulated in Section 2.6 of the TCP Guidebook from Thesis 1 until Thesis 2.

Furthermore, I agree to set the schedule for advising or consultation to help the students and ensure the success of the thesis.

Conformed:

Ma. Allaine C. Agna
Name and Signature

APPENDIX L

THESIS/CAPSTONE TITLE APPROVAL FORM

FINAL PROJECT TITLE FORM

Team Alias:
Proponents/Researchers:

1) Aurellano, Divino Franco
2) Avila, Herald Carl
3) Calingacion, Almira

Proposed Thesis/ Capstone Project Title:

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

Submitted by: **Aurellano, Divino Franco R.** (Signature of Project Head over printed name) Date: _____	**Noted:** **ROSEL O. ONESA, MIT** (Signature of Subject Adviser over printed name) Date: Feb 13, 2025
Recommending Approval: **ROSEL O. ONESA, MIT** (Signature of Thesis Adviser over printed name) Date: Feb 13, 2025	**Approved:** **ROSEL O. ONESA, MIT** OIC DEAN, CCS Date: Feb 13, 2025

*** Accomplished in 3 copies

APPENDIX M

THESIS/CAPSTONE HEARING FORM (TD, POD, FOD)

THESIS HEARING FORM

Date Filed: **May 5, 2025** [/] Title Proposal [☐] Pre-Oral [☐] Final Oral

Date of Hearing: May 5, 2025 Time: 10: 30 - 12:30 PM Venue: Conference Room

Department: **COLLEGE OF COMPUTER STUDIES (CCS)**

Research Title:
BEYOND LLMs: A RAG CHATBOT FOR EFFICIENT LITERATURE SEARCH AND THESIS RETRIEVAL IN CSPC LIBRARY

Proponent/s:

AURELLANO, DIVINO FRANCO **CALINGACION, ALMIRA**

AVILA, HERALD CARL

Recommended by:

ROSEL O. ONESA, MIT
Thesis Adviser

CERTIFICATION

The undersigned members comprising the panel for oral examination hereby agree to the schedule of hearing for the above research.

TIFFANY LYN O. PANDES, MSc
PANEL MEMBER 1

KAELA MARIE N. FORTUNO, MIT
PANEL MEMBER 2

JOSEPH JESSIE S. OÑATE, MSc
PANEL CHAIR

NOTED BY:

TIFFANY LYN O. PANDES, MSc
Subject Adviser

APPROVED:

ROSEL O. ONESA, MIT
OIC Dean, CCS

THESIS HEARING FORM

Date Filed: **October 17, 2025** [☐] Title Proposal [/] Pre-Oral [☐] Final Oral

Date of Hearing: October 20, 2025 Time: 4:30 - 6:30 PM Venue: Conference Room

Department: **COLLEGE OF COMPUTER STUDIES (CCS)**

Research Title:

BEYOND LLMs: A RAG CHATBOT FOR EFFICIENT LITERATURE SEARCH AND THESIS RETRIEVAL IN CSPC LIBRARY

Proponent/s:

AURELLANO, DIVINO FRANCO
CALINGACION, ALMIRA
AVILA, HERALD CARL

Recommended by:

Ms. Rosel O. Onesa, MIT
Thesis Adviser

CERTIFICATION

The undersigned members comprising the panel for oral examination hereby agree to the schedule of hearing for the above research.

TIFFANY LYN O. PANDES, MSc
PANEL MEMBER 1

KAELA MARIE N. FORTUNO, MIT
PANEL MEMBER 2

JOSEPH JESSIE S. OÑATE, MSc
PANEL CHAIR

NOTED BY:

TIFFANY LYN O. PANDES, MSc
Subject Adviser

APPROVED:

ROSEL O. ONESA, MIT
OIC Dean, CCS

THESIS HEARING FORM

Date Filed: **December 5, 2025** [☐] Title Proposal [☐] Pre-Oral [/] Final Oral

Date of Hearing: December 9, 2025 Time: 1: 00 - 2: 00 PM Venue: Conference Room

Department: **COLLEGE OF COMPUTER STUDIES (CCS)**

Research Title:

BEYOND LLMs: A RAG CHATBOT FOR EFFICIENT LITERATURE SEARCH AND THESIS RETRIEVAL IN CSPC LIBRARY

Proponent/s:

AURELLANO, DIVINO FRANCO **CALINGACION, ALMIRA**

AVILA, HERALD CARL

Recommended by:

ROSEL O. ONESA, MIT
Thesis Adviser

CERTIFICATION

The undersigned members comprising the panel for oral examination hereby agree to the schedule of hearing for the above research.

TIFFANY LYN O. PANDES, MSc
PANEL MEMBER 1

KAELA MARIE N. FORTUNO, MIT
PANEL MEMBER 2

JOSEPH JESSIE S. OÑATE, MSc
PANEL CHAIR

NOTED BY:

TIFFANY LYN O. PANDES, MSc
Subject Adviser

APPROVED:

ROSEL O. ONESA, MIT
OIC Dean, CCS

APPENDIX N

PANEL RSC (TD, POD, FOD)

Republic of the Philippines
Camarines Sur Polytechnic Colleges
Nabua, Camarines Sur
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COLLEGE *of* COMPUTER STUDIES

Title : **BEYOND LLMS: A RAG CHATBOT FOR EFFICIENT LITERATURE SEARCH AND THESIS RETRIEVAL IN CSPC**

Alias : TEAM VIRGO

Date : MAY 05 2025, 10:30 AM ☒ TD ☐ POD ☐ FOD

Secretary : JELAND O. ALBONIAL

MANUSCRIPT			
CHAPTER	**PAGE NO.**	**RECOMMENDATIONS, SUGGESTIONS AND COMMENT (RSC)**	**ACTION TAKEN**
1, 2, 3	2, 26	Consistency of the term used. (Prototype or System) choose one	We change the term prototype into system consistently throughout the manuscript
	26	The tone should be in the future tense	We reviewed each section and changed all past tense into future tense,(like, will be), especially in chapter 3.
	20, 29	Remove the hanging page.	We recompiled the LaTex file and reformatted the content to ensure there are no hanging pages.
	27, 30, 41	Add a vector database, then retrain the model.	We added the FAISS vector database but not retraining since. Instread of retraining we put embedding
	10, 22, 43	Proper ACM formatting specifically the bracket.	We followed the ACM formatting guide (Minified Cookbook in Thesis) and corrected the brackets accordingly
	26	Avoid using first-person pronouns.	We revised the manuscript to avoid first-person pronouns, using objective phrasing instead.
2	21	Revise the gap at least 2 paragraphs and include how to address study.	We revised the gap to two clear paragraphs and we also added a detailed explanation of how the study addresses the identified gap
	18, 19	Include the evaluation metrics used, along with the results, in the assessment of the RAG system.	We included evaluation metrics (context precision, context recall, faithfulness) and summarized their reported results in the literature review.
	18, 19	Include the findings identified in the review of related literature	We added key findings from the literature review into the evaluation matrix
3	39, 40, 41, 42	Discuss the flow of the conceptual framework	We expanded the conceptual framework discussion by clearly presenting the flow of the system
	26	In Methodology, the sectioning is confusing, so it needs to be fixed	We reorganized the methodology into clear subsections with logical flow
	26	In Methodology, emphasize empirical research and how specifically this will be used in your study	We remove the empirical and change it into a constructive approach
	26	Remove the research method	We removed the redundant "Research Method" section as recommended.
	29	Increase the number of datasets to enhance efficiency	We expanded the dataset size to all available PDF thesis documents that can be only provided by them and sourced from the CSPC Library
	36, 27	Place the precision equation under Precision K on page 34	We already placed the precision equation under the precision k.
	26	Ensure that the research design and methods are constructive	We revised the research design and methodology to be constructive.

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	26	Make an introduction to research design and expand and explain the second paragraph	We added an introduction to research design and elaborated on the second paragraph for a better explanation
	33, 35, 42	Include the usability of the chatbot	The usability evaluation of the chatbot is included in our assessment. In Chapter 3, we mention using a user evaluation questionnaire to gather feedback on usability, accuracy, and overall satisfaction, applying a 5-point Likert scale.
	31, 32,33	Add a statistical tool and also include the questionnaire under the instruments section.	We added the statistical tool, and an evaluation questionnaire on instruments section.
3	26	**Revised chapter 3 methodology part**	We revised Chapter 3 methodology thoroughly to incorporate all suggested improvements.

SOFTWARE PROGRAM/ PROTOTYPE		
MODULE NO. (DFD)	**RECOMMENDATIONS, SUGGESTIONS, AND COMMENTS (RSC)**	**ACTION TAKEN**

NOTED BY:

JOSEPH JESSIE OÑATE, S. MSc
PANEL, CHAIRMAN

TIFFANY LYN O. PANDES, MSc.
PANEL, MEMBER 1

KAELA MARIE T. FORTUNO, MIT
PANEL, MEMBER 2

APPENDIX O

CONSULTATION LOG FORM (CLF)

CONSULTATION LOGS FORM

Thesis Title:	Beyond LLMs: A RAG Chatbot for Efficient Literature Search and Thesis Retrieval in CSPC Library						
Proponents:	Aurellano, Divino Franco, Avila, Herald Carl, Calingacion, Almira						
Alias:	Team Virgo						
Total # of Modules:				**as approved by the CAPSA /TSA:**			
PROTOTYPE	**Date of Consultation**	**# of Modules Fully Implemented**	**# of Modules Partially Implemented**	**Running Score**	**Percentage**	**Project Heads's Signature**	**TA/TSA/ Adviser Signature**
Checking for Manuscript	12-05-25						
	Remarks: – include findings in the Abstract – include ACM – additional respondents – label sections in Chapter 4 replacing each items in the SO – sample SS of questionnaire						
Deadline: 12-05-2025							

CONSULTATION LOGS FORM

Thesis Title:	Beyond LLMs: A RAG Chatbot for Efficient Literature Search and Thesis Retrieval in CSPC Library						
Proponents:	Aurellano, Divino Franco, Avila, Herald Carl, Calingacion, Almira						
Alias:	Team Virgo						
Total # of Modules:				**as approved by the CAPSA /TSA:**			
PROTOTYPE	**Date of Consultation**	**# of Modules Fully Implemented**	**# of Modules Partially Implemented**	**Running Score**	**Percentage**	**Project Heads's Signature**	**TA/TSA/ Signature**
Checking for prototype and papers	10-3-25				60%		
	Remarks: - change verb form into past form (chpt 3-4) - Revise chapter 3 - include methods/process - Revise chapter 4 based on objectives - Revise chapter 5						
Deadline: 10-3-2025							

CONSULTATION LOGS FORM

Thesis Title:	Beyond LLMs: A RAG Chatbot for Efficient Literature Search and Thesis Retrieval in CSPC Library						
Proponents:	Aurellano, Divino Franco, Avila, Herald Carl, Calingacion, Almira						
Alias:	Team Virgo						
Total # of Modules:				**as approved by the CAPSA /TSA:**			
PROTOTYPE	**Date of Consultation**	**# of Modules Fully Implemented**	**# of Modules Partially Implemented**	**Running Score**	**Percentage**	**Project Heads's Signature**	**TA/TSA/ Signature**
Checking for prototype and papers	10-10-25						
	Remarks: Good for PDD !! Good Luck.						
Deadline: 10-10-2025							

CONSULTATION LOGS FORM

Thesis Title:	Beyond LLMs: A RAG Chatbot for Efficient Literature Search and Thesis Retrieval in CSPC Library						
Proponents:	Aurellano, Divino Franco, Avila, Herald Carl, Calingacion, Almira						
Alias:	Team Virgo						
Total # of Modules:				**as approved by the CAPSA /TSA:**			
PROTOTYPE	**Date of Consultation**	**# of Modules Fully Implemented**	**# of Modules Partially Implemented**	**Running Score**	**Percentage**	**Project Heads's Signature**	**TA/TSA/ ~~Consultant~~ Signature**
Checking for prototype and papers	10-2-25						
	Remarks: Improve the retrieval of chunks and context of the response.						
Deadline: 10-2-2025							

CONSULTATION LOGS FORM

Thesis Project Title		Beyond LLMs: A RAG Chatbot for Efficient Literature Search and Thesis Retrieval in CSPC Library					
Proponents:		Aurellano, Divino Franco			Avila, Herald Carl		
Alias:	TEAM VIRGO	Calingacion, Almira					
Total # of Modules				as approved by the TSA			
PROTOTYPE	**DT of Consultation**	**# of Modules Fully Implemented**	**# of Modules Partially Implemented**	**Running Score**	**Percentage**	**Project Manager's Signature**	**TA/TSA/ Grammarian Signature**
(Replace this about the Activity to be Consulted) Revision by Grammarian about the grammatical error of BSC							Ma. Allayne G. Agna
	Remarks The thesis was thoroughly reviewed, ensuring clarity and minor grammatical errors, also precision language. The minor grammatical errors were corrected enhancing the overall professionalism of the work. the revision have significantly improved the readability and flow of the document.						
Deadline:							
(Replace this about the Activity to be Consulted) Revision of chapter 2 based of BSC							
	Remarks						
Deadline:							

*** Must attach with this form your chosen Data and Process Model (IT) or Algorithm Model (CS)

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APPENDIX Q

LANGUAGE EDITING CERTIFICATION

This is to certify that the undersigned has reviewed and went through all the pages of the Bachelor of Science in Computer Science thesis manuscript titled **"BEYOND LLMS: A RAG CHATBOT FOR EFFICIENT LITERATURE SEARCH AND THESIS RETRIEVAL IN CSPC LIBRARY"** of **Divino Franco R. Aurellano, Herald Carl N. Avila, Almira L. Calingacion**, as against the set of structural rules that govern research writing in accord with the composition of sentences, phrases, and words in the English language.

MA. ALLAINE C. AGNA, LPT

Grammarian

Date: 12-19-2025

APPENDIX P

SECRETARY'S CERTIFICATION

This is to certify that the undersigned has provided accurate recommendations, suggestions, and comments unanimously agreed and approved by the panel of examiners during the oral examination of the thesis titled

"BEYOND LLMS: A RAG CHATBOT FOR EFFICIENT LITERATURE SEARCH AND THESIS RETRIEVAL IN CSPC LIBRARY"

prepared and submitted by **Aurellano, Divino Franco R.**, **Avila, Herald Carl N.**, **Calingacion, Almira L.**, and that the same have not been amended, modified or obliterated.

MS. MARRI GRACE MORATA

Secretary

Date:_____

APPENDIX Q

CERTIFICATE OF TRANSFER

CAMARINES SUR POLYTECHNIC COLLEGES
COLLEGE of COMPUTER STUDIES

CERTIFICATE

OF TRANSFER

This certify that "Beyond LLMs: A Rag Chatbot for Efficient Search Literature and Thesis Retrieval in CSPC Library" developed by Divino Franco R. Aurellano, Herald Carl N. Avila and Almira L. Calingacion, Camarines Sur Polytechnic Colleges (CSPC) - College of Computer Studies (CCS) students, as their undergraduate thesis project was transferred to the CCS Dean's Office, Camarines Sur Polytechnic Colleges for further research.

This Certification is issued this 7 day of January 2026 at CCS Dean's Office for whatever legitimate purpose it may serve.

ROSEL O. ONESA, MIT
OIC DEAN, CCS

APPENDIX R

CERTIFICATE OF PLAGIARISM CHECK

CERTIFICATION

Date of Release:	January 12, 2026
Submission ID:	23367:125916216
Output Title:	BEYOND LLMS: A RAG CHATBOT FOR EFFICIENT LITERATURE SEARCH AND THESIS RETRIEVAL IN CSPC LIBRARY
Author(s):	Divino Franco R. Aurellano Almira L. Calingacion Herald Carl N. Avila
Program:	Bachelor of Science in Computer Science

Authenticity Report:

Similarity Index Report: **15%**

Internet Sources: *2%*

Publications: *2%*

Student Papers: *14%*

- *Interpretation:* The similarity index report means that **15%** of the output is similar to the sources in Turnitin's (authenticity software) online repository and databases

AI-Generated Report: ***26%***

AI-generated only: *26%*

AI-generated text that was AI-paraphrased: *0%*

- *Interpretation:* The AI generated report means that **26%** of the output indicates a *likely* AI-generated text and *likely* AI-paraphrased text, which is ***within the acceptable AI usage*** in the field of Engineering.

HAROLD JAN R. TERANO, Ph.D.
Director, Research & Development Services Office

APPENDIX S

CERTIFICATION FOR GPU SERVER USAGE

CAMARINES SUR POLYTECHNIC COLLEGES
ISO 9001:2015 Certified

AI RESEARCH CENTER for COMMUNITY DEVELOPMENT

CERTIFICATION

This is to certify that the GPU server is utilized for training AI and machine learning models in the study titled "Beyond LLMs: A RAG Chatbot for Efficient Literature Search and Thesis Retrieval in CSPC Library" by Divino Franco R. Aurellano, Herald Carl N. Avila, and Almira L. Calingacion (Team Virgo), which has been reviewed and verified by the AIRCODE office.

This certification is issued on January 8, 2026 by the office of AIRCODE at Camarines Sur Polytechnic Colleges, Nabua, Camarines Sur.

JOSEPH JESSIE S. OÑATE, MSc
Head, AIRCODE

APPENDIX T

ACM FORMAT

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

Divino Franco R. Aurellano*
diaurellano@my.cspc.edu.ph
Camarines Sur Polytechnic Colleges
Nabua, Camarines Sur, Philippines

Herald Carl N. Avila†
heavila@my.cspc.edu.ph
Camarines Sur Polytechnic Colleges
Nabua, Camarines Sur, Philippines

Almira L. Calingacion‡
alcalingacion@my.cspc.edu.ph
Camarines Sur Polytechnic Colleges
Nabua, Camarines Sur, Philippines

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 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

ACM Reference Format:
Divino Franco R. Aurellano, Herald Carl N. Avila, and Almira L. Calingacion. 2024. Beyond LLMs: A RAG Chatbot for Efficient Literature Search and Thesis Retrieval in CSPC Library. In *Proceedings of Proceedings of the ACM Hypertext Conference (Hypertext '26).* ACM, New York, NY, USA, 6 pages. https://doi.org/XXXXXXX.XXXXXXX

1 INTRODUCTION

The rapid advancements in Natural Language Processing (NLP) have revolutionized information retrieval, enabling more efficient and context-aware systems. Large Language Models (LLMs), such as OpenAI's ChatGPT and Google Gemini, have demonstrated remarkable capabilities in semantic understanding and generation. However, LLMs face inherent limitations in accessing real-time or domain-specific institutional data, which restricts their effectiveness in specialized tasks such as academic literature retrieval. Retrieval-Augmented Generation (RAG) addresses this limitation by integrating LLMs with external knowledge sources, enabling factually grounded responses. Studies by [13] and [14] demonstrate that RAG-augmented LLMs significantly improve accuracy and coherence in knowledge-intensive tasks. Furthermore, [7] highlighted vector databases for semantic indexing, which enhance retrieval efficiency, a capability essential for thesis discovery in academic libraries.

University libraries, including the CSPC Library, maintain extensive collections of undergraduate theses that serve as valuable academic resources. However, these institutions typically rely on traditional, non-digital search systems with restrictive access policies. Physical theses cannot be removed from library premises, and keyword-based catalogs fail to capture semantic intent, resulting in incomplete or irrelevant search results. This limitation hinders student and researcher access to critical academic materials, impeding research progress and academic development.

This study addresses these challenges by developing a Retrieval-Augmented Generation (RAG)-based chatbot integrated with a Large Language Model to enable efficient, semantic-driven thesis discovery. The primary objectives are: (1) to design and implement a RAG pipeline that processes and indexes 290+ thesis PDFs using semantic embeddings and a FAISS vector database; (2) to develop a conversational interface enabling natural language queries for thesis retrieval; (3) to evaluate system performance using the RAGAS framework and user-centered assessment; and (4) to demonstrate that AI-driven retrieval systems significantly improve literature accessibility, search efficiency, and user satisfaction compared to traditional library systems. This research advances information retrieval in academic settings, providing students and researchers with a modern tool for thesis discovery and supporting institutional knowledge management.

2 BACKGROUND

Retrieval-Augmented Generation (RAG) is a technique that combines information retrieval with natural language generation to enhance the capabilities of Large Language Models. RAG systems retrieve relevant external documents or data during inference and use this context to ground the model's responses, thereby reducing hallucinations and improving factual accuracy. This approach is particularly valuable in knowledge-intensive tasks where up-to-date or domain-specific information is required. Large Language Models (LLMs) with integrated RAG techniques have greatly improved knowledge-intensive NLP tasks, overcoming traditional LLM limitations. Studies by [13] and [14] demonstrate how combining RAG with LLMs significantly improves accuracy and coherence in conversations and complex queries. Furthermore, [7] highlighted the use of vector databases for continuous information adaptation integrated with RAG, greatly enhancing retrieval efficiency and relevancy of LLM outputs, which is essential for literature search and thesis retrieval in university libraries. Vector databases such as FAISS (Facebook AI Similarity Search) are specialized data structures designed to store and retrieve high-dimensional vector embeddings efficiently, enabling semantic similarity-based retrieval that

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https://doi.org/XXXXXXX.XXXXXXX

captures the meaning and intent of queries, resulting in more contextually relevant results compared to traditional keyword-based search.

The application of RAG in various domains has been extensively explored and demonstrates significant potential for transforming information retrieval across diverse fields. For instance, Arzideh et al. 2024 incorporated clinical language embeddings within RAG to improve healthcare information retrieval, while Grigoryan and Madoyan 2024 presented a system that enhances academic retrieval using vector search. Additionally, Aquino et al. 2024 employed RAG for effectively extracting and analyzing Brazilian legal documents, and Ryu et al. 2023 validated RAG's effectiveness in legal question-answering tasks. Evaluation metrics are crucial for assessing RAG system performance, with the RAGAS (RAG Assessment) framework providing automated metrics including Context Precision, Context Recall, Answer Relevancy, and Faithfulness, as emphasized by [11] and [2]. Despite the effectiveness of automated metrics, human evaluation remains important in assessing coherence and user satisfaction [1], providing complementary insights into system usability and effectiveness.

3 METHODOLOGY

This study employed a constructive research design to develop and evaluate a Retrieval-Augmented Generation (RAG)-based chatbot system integrated with a Large Language Model (LLM). The system aimed to enhance thesis literature retrieval within the CSPC Library by replacing traditional keyword-based search with a vector database and conversational framework. The chatbot was deployed to the cloud for accessibility.

3.1 Data Sources

The dataset comprised 290+ undergraduate thesis PDFs sourced from multiple departments within the CSPC library. These documents were provided by library personnel under agreed-upon data handling protocols. The dataset included theses from various academic disciplines, ensuring a diverse and comprehensive knowledge base.

3.2 Instruments

In this subsection, introduced the instruments that was used by researchers to analyze and evaluate the performance of the RAG chatbot system.

RAGAS (Retrieval-Augmented Generation Assessment Suite). toolkit was utilized to automatically evaluate the quality of system outputs using metrics such as context precision, faithfulness, and answer relevance [12]. Furthermore, a context recall metric was included, as recommended for evaluating retrieved chunks. These instruments ensured a rigorous and balanced evaluation of the proposed system from both system-level and user perspectives [8].

Survey. Instruments served as data collection tools across different areas and provided an effective way to gather information. They were useful when seeking insights into the attributes, preferences, opinions, or beliefs of a specific group. To meet the study objectives, the researchers conducted a survey among employed librarians and CSPC 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. The researchers developed questionnaires 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. The respondents of the study were all from the CSPC including 2 employees of Library, 2 faculty, and 14 students who served as a representative of the whole population.

3.2.1 RAG Pipeline. The Retrieval-Augmented Generation (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.

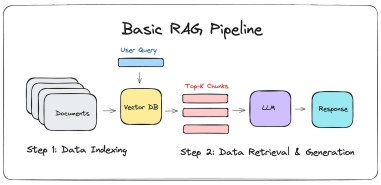

Figure 1: Basic RAG Pipeline by Dr. Julija

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

- **Document Ingestion and Preprocessing:** Thesis PDFs are ingested, and their texts are extracted, enriched with metadata, and segmented into coherent chunks using token-based chunking that respects academic structure (Abstract; Chapters 1–5) to preserve semantic context.
- **Data Indexing:** Text chunks are converted into dense vectors using 'sentence-transformers/all-MiniLM-L6-v2', chosen for its lightweight architecture and strong semantic representation capabilities. These vectors and metadata are indexed in FAISS for efficient similarity search and scalable retrieval over the thesis corpus.
- **Query Processing and Retrieval:** User queries are embedded using the same model employed for indexing. A FAISS-backed retriever performs semantic search to return the top-K most relevant chunks (default $K = 50$), balancing precision and recall based on semantic similarity.
- **Response Generation with LLM:** Retrieved chunks are provided to the Gemini 2.5-flash language model as grounded context. This advanced LLM, part of the Gemini 2.X family, generates factually accurate and relevant responses aligned with source documents, leveraging its optimized architecture for low latency and domain-specific retrieval.
- **User Interface and Deployment:** The system is deployed to the cloud with a web interface for user interaction, displaying responses along with metadata for transparency and traceability.

3.3 Procedures

The study followed a structured approach to develop and deploy the RAG-based chatbot system. First, data preprocessing was conducted by extracting texts from thesis PDFs on a page-by-page basis and enriching them with metadata, such as source and page numbers. Token-based chunking was then applied to segment the texts into coherent pieces aligned with thesis sections (e.g., Abstract, Chapters 1–5), ensuring compatibility with the LLM's context window and improving retrieval fidelity. A sample of the CSPC thesis PDFs used in this process is shown in Figure 2.

Next, indexing and vector database construction involved embedding text chunks into dense vectors using sentence-transformers/all-MiniLM-L6-v2 and indexing them in FAISS for semantic search. During query handling, user queries were encoded and matched against the vector database to retrieve the top-K relevant chunks based on semantic similarity. The Gemini 2.5-flash model then generated responses grounded in the retrieved context, ensuring factual accuracy and relevance. These responses were displayed via a web interface with metadata for transparency. The system's performance was assessed using both automated metrics from the

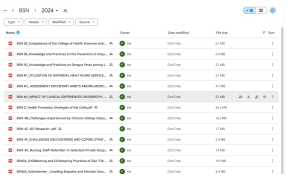

Figure 2: CSPC Thesis PDF Sample

RAGAS framework and a user questionnaire with a 5-point Likert scale to evaluate human-centered performance.

3.4 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:

3.4.1 Context Precision. Measured the relevance of retrieved chunks.

$$\text{Precision@k} = \frac{\text{true positives@k}}{\text{true positives@k} + \text{false positives@k}} \tag{1}$$

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.

3.4.2 Context Recall. Assessed the comprehensiveness of retrieval.

$$\text{Context Recall} = \frac{\text{Number of relevant claims supported by retrieved chunks}}{\text{Total number of relevant claims in the reference answer}} \tag{2}$$

where:

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

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

$$\text{Response Relevance} = \frac{1}{N}\sum_{i=1}^{N}\cos(E_{g_i}, E_o) \tag{3}$$

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.

3.4.4 Faithfulness. Ensured factual consistency with retrieved context.

$$\text{Faithfulness} = \frac{\text{Number of claims in the response supported by retrieved context}}{\text{Total number of claims in the response}} \tag{4}$$

where:

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

3.5 Conceptual Framework

The conceptual framework of this study is illustrated in Figure 3.

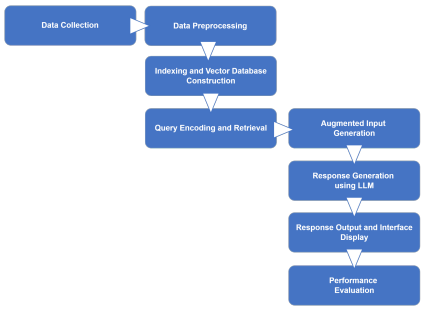

Figure 3: Conceptual Framework

3.5.1 Data Collection. The process began with coordination between the researchers and CSPC Library staff, where the prototype was demonstrated to illustrate how a RAG-powered chatbot could improve thesis discovery beyond exact-keyword search by enabling topic-oriented, semantically grounded retrieval within the library's own repository. In the demonstration, the project's institutional value was emphasized in accelerating literature searches, increasing access to relevant local theses, and supporting academic guidance. Following this formal presentation, the researchers submitted a request to obtain all undergraduate thesis PDFs from various College departments of CSPC to use as the main corpus of the RAG chatbot application.

3.5.2 Data Pre-processing. Tools such as PyMuPDF were employed to extract plain text from the collected PDFs. The extracted content underwent cleaning and normalization to remove non-informative characters, followed by segmentation into semantically meaningful text chunks that preserved the structural integrity of academic documents.

3.5.3 Indexing and Vector Database Construction. Each text chunk was embedded using the 'sentence-transformers/all-MiniLM-L6-v2' model from Hugging Face, converting semantic meanings into dense vectors that capture both explicit and implicit relationships across CSPC thesis documents. These vectors were indexed in FAISS, enabling fast, context-aware retrieval of relevant content through natural language queries. Metadata was preserved for each vector, maintaining links to source documents and positions, thereby supporting semantic discovery of academic literature and surpassing traditional keyword matching approaches.

3.5.4 Query Encoding and Retrieval. User queries were encoded into dense vectors using the same embedding model as employed for document indexing, ensuring semantic alignment. The system then performed fast similarity searches in FAISS, retrieving the top-K relevant thesis chunks based on conceptual match rather than keyword overlap. This process allowed contextually accurate results even for varied terminology, forming the basis for the chatbot's informed, thesis-grounded responses.

3.5.5 Augmented Input Generation. The augmented input generation phase served as the crucial bridge between retrieved thesis content and intelligent response formulation, where raw document chunks evolved into contextually enriched prompts capable of guiding accurate academic discourse.

3.5.6 Response Generation. The response generation stage represented the culmination of the RAG pipeline, where the Gemini 2.5-flash model transformed augmented academic context into coherent, factually grounded answers that addressed user research inquiries with precision and relevance.

3.5.7 Response Output and Interface Display. Flask was used to create an intuitive web interface that presented the chatbot's responses alongside relevant metadata, such as source thesis titles and sections, ensuring transparency and traceability of retrieved information.

3.5.8 Performance Evaluation. The system's effectiveness was evaluated using two complementary approaches: automated RAGAS metrics (context precision, context recall, answer relevance, and faithfulness) and a user survey using Likert scales. Findings from both evaluation methods guided refinements to retrieval strategies, prompting techniques, and user interface design. This dual-evaluation approach ensured technical robustness, usability, and trustworthy, thesis-grounded answers aligned with CSPC academic needs for library users and researchers.

4 RESULTS AND DISCUSSION

4.1 Document Ingestion and Retrieval Module

The study processed 290+ undergraduate thesis PDFs from the CSPC Library into a dynamic, searchable knowledge base. Texts were extracted, enriched with metadata, and segmented into 38,127 coherent chunks, averaging 311 tokens per chunk. These chunks were embedded using 'sentence-transformers/all-MiniLM-L6-v2' and indexed in FAISS for efficient semantic retrieval. This process ensured compatibility with the RAG pipeline and improved retrieval fidelity. The chunking strategy and semantic indexing played a critical role in ensuring the fidelity and transparency of the retrieved information.

4.2 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.

4.2.1 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.

4.2.2 Augmented Input and Generation. Retrieved chunks were concatenated with the user query into a structured context with lightweight citation markers. This supported grounded, traceable answers and reduced hallucination risk. Prompt templates guided the model to answer strictly from provided context, with safeguards (token monitoring, truncation) to maintain input quality.

4.2.3 Response Generation with Gemini 2.5-flash. The Gemini 2.5-flash model generated answers grounded in retrieved context. The system was configured with temperature=0 to ensure deterministic outputs suitable for academic use. Generated content was parsed into clean text for display. While RAG significantly reduced hallucinations, occasional inaccuracies were observed when context was insufficient; users were advised to validate critical findings. The Flask-based web interface facilitated user interaction, providing clear and traceable responses.

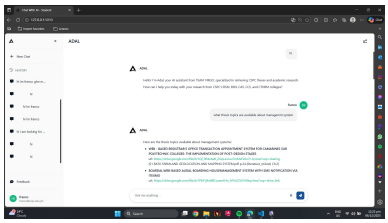

Figure 4: User Interface

In Figure 4, the system was deployed to the cloud to ensure accessibility for users across various locations. The interface supports conversational exploration with session-based history and safety filters for disallowed queries. Generated responses appear as Markdown with citations and structured text. When queries violate safety parameters, clear warnings are displayed. Deterministic settings improve consistency and build user trust.

4.3 Evaluation Results

4.3.1 Automated Evaluation Metrics. The system was evaluated using the RAGAS framework, focusing on four core metrics: Answer Relevancy, Context Precision, Context Recall, and Faithfulness. Table 1 summarizes the results.

Table 1: RAG System Evaluation Metrics using RAGAS Framework

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

The table presents a performance profile characterized by precise, well-grounded answers. Faithfulness (0.9179) and Context Precision (0.9167) indicate that retrieved evidence is both accurate and tightly focused, yielding citations that trace cleanly to source pages. Context Recall (0.8711) shows broad coverage of relevant thesis passages, while Answer Relevancy (0.8625) confirms that final responses align with user intent in typical literature-search tasks.

In practice, a query such as "What methodologies are used for detecting academic plagiarism at CSPC?" returns a compact set of segments drawn from Methods and Related Works sections across multiple theses. The system synthesizes these into direct, cited responses; high precision keeps noise low, high recall surfaces cross-department perspectives, and high faithfulness maintains strict grounding in the referenced documents.

These results demonstrate the RAG system's effectiveness in retrieving and generating accurate, relevant, and well-grounded answers based on the indexed thesis documents from the CSPC Library. The high scores across all four evaluation metrics indicate that the system is capable of providing reliable academic assistance, making it a valuable tool for students and researchers seeking information from the library's thesis collection.

4.4 Visualization of RAG System Evaluation Metrics

The bar chart in Figure 5 illustrates the performance of the RAG system across all four evaluation metrics. Faithfulness achieved the highest score at 0.9179, indicating that the system's responses are strongly grounded in retrieved context, with minimal hallucinations or unsupported claims. Context Precision followed closely at 0.9167, demonstrating that retrieved chunks are highly relevant to user queries, minimizing noise in the retrieval results. Context Recall scored 0.8711, reflecting comprehensive coverage of relevant thesis segments necessary to answer user questions. Answer Relevancy, at 0.8625, shows strong alignment between generated responses and original user queries, confirming that the system effectively interprets user intent and provides pertinent information.

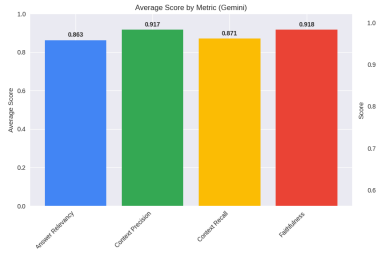

Figure 5: Bar Chart of RAG System Evaluation Result

The consistency of high scores across all metrics validates the RAG system's robustness in delivering accurate, relevant, and well-grounded responses. This balanced performance profile is particularly important for academic applications, where factual accuracy and comprehensive coverage are critical. The slightly lower Context Recall score suggests minor gaps in retrieval completeness, which could be addressed through optimization of chunk size, retrieval parameters, or refinement of the embedding model. Nevertheless, these results demonstrate that the RAG-augmented chatbot is reliable for thesis discovery and academic information retrieval within the CSPC Library context.

4.4.1 User-Centered Evaluation. A user-centered evaluation was conducted using a 5-point Likert scale questionnaire with 101 respondents (2 library employees, 2 faculty members, and 97 students). Table 2 summarizes the results.

Table 2: User Agreement: Chatbot Response Quality and Performance

Criteria	Weighted Mean	Verbal Interpretation
The questions are answered well by the chatbot.	4.3	Strongly Agree
The answers are relevant to the question.	4.5	Strongly Agree
Chatbot's responses are clear and understandable.	4.5	Strongly Agree
The chatbot's responses help answer your questions.	4.3	Strongly Agree
The chatbot provided enough information.	4.2	Strongly Agree
The chatbot has a quick response time.	4.1	Agree
Overall Weighted Mean	**4.3**	**Strongly Agree**

The results of the evaluation of the RAG-based chatbot using a user-centered evaluation method indicate a generally positive reception from users across all assessed criteria. Overall, the findings show that users strongly agreed that the chatbot effectively supported their information needs, particularly in terms of accuracy, relevance, clarity, and responsiveness. In terms of question-and-answer performance, users strongly agreed (weighted mean: 4.3) that the chatbot performed well in answering their questions, indicating that the system met user expectations in providing correct responses. Similarly, users strongly agreed (weighted mean: 4.5) that the answers provided were relevant to their queries, suggesting that the chatbot effectively interpreted user intent and retrieved appropriate information.

Another strong result was observed in response clarity, where users strongly agreed (weighted mean: 4.5) that the chatbot delivered clear and easy-to-understand explanations. This implies that the system not only provides accurate answers but also presents them in a user-friendly manner. Moreover, users strongly agreed (weighted mean: 4.3) that the chatbot helped them find the information they were looking for, demonstrating its usefulness in supporting user tasks.

The system was also perceived as sufficiently informative, with users strongly agreeing (weighted mean: 4.2) that the chatbot provided complete and helpful responses during interactions. In terms of system responsiveness, users agreed (weighted mean: 4.1) that the chatbot responded quickly, allowing them to access information without unnecessary delay. Overall, the evaluation results yielded an average weighted mean of 4.3, corresponding to a "Strongly Agree" rating. This indicates that users generally found the chatbot's responses to be accurate, relevant, clear, and timely. These findings suggest that the chatbot performs effectively in its primary role of assisting users with information retrieval. However, minor improvements in response completeness and speed could further enhance user satisfaction. Furthermore, as noted by Følstad et al. (2021), user-centered evaluation plays a crucial role in understanding user needs and experiences, reinforcing the importance of this method in assessing chatbot effectiveness prior to deployment.

4.4.2 User Feedback on RAG chatbot's Effectiveness and Usability. 3 presents the user-centered evaluation results of the RAG chatbot using a 5-point Likert scale. The table shows weighted means for user satisfaction, likelihood of using the chatbot again, ease of reading and understanding the chatbot's output, and confidence in the chatbot's information, allowing readers to gauge overall user perception and intent to use the system in the future.

Table 3: User Feedback on RAG chatbot's Effectiveness and Usability

Criteria	Weighted Mean	Verbal Interpretation
Satisfaction with answers	4.1	Satisfied
Likelihood of using the chatbot again	4.3	Very Likely
Ease of understanding the chatbot's output	4.5	Very Easy
Confidence in the chatbot's information	3.8	Confident
Overall Weighted Mean	**4.2**	**Strongly Agree**

The results for satisfaction with answers, likelihood to use again, ease of reading and understanding, and confidence in information

accuracy show generally positive user feedback. And, according to Kaushal and Yadav 2022 and Okonkwo and Ade-Ibijola 2021, these aspects of chatbots that deliver clear, useful, and readable responses greatly improve user satisfaction. In addition, Choudhury and Shamszare 2023 and Zhang et al. 2024 found that trust and factual accuracy are essential for encouraging continued use and building user confidence in AI chatbots. After considering these established determinants, the detailed breakdown is as follows. In terms of user satisfaction with answers, users were satisfied (weighted mean: 4.1), indicating that the chatbot's replies met users' needs and were generally acceptable. Regarding likelihood of reuse, users were very likely to use the chatbot again (4.3), suggesting strong perceived utility. Users also found the responses very easy to read and understand (4.5), demonstrating clear and user-friendly output. Confidence in the chatbot's information was moderately strong (3.8), implying general trust with some expectation for accuracy improvements. Overall, resppondents gave positive feedback, with an overall weighted mean of 4.2, indicating useful, relevant, clear, mostly complete answers, strong reuse intent, good experience, and improving factual confidence as priority.

5 CONCLUSION

This study successfully demonstrated the feasibility and effectiveness of a Retrieval-Augmented Generation (RAG)-based chatbot system in enhancing thesis literature search and retrieval within the CSPC Library. By integrating semantic embeddings, vector database indexing, and Large Language Models, the system addressed critical limitations of traditional keyword-based search methods.

The findings reveal that the RAG chatbot delivers significant technical and user-centered benefits. Automated evaluation using the RAGAS framework confirmed strong performance, with Faithfulness and Context Precision exceeding 0.91, while Context Recall (0.8711) and Answer Relevancy (0.8625) demonstrated comprehensive and relevant retrieval capabilities. Complementary user-centered evaluation with 18 respondents yielded an overall weighted mean of 4.3 (Strongly Agree), affirming that users found responses accurate, relevant, clear, and appropriately comprehensive, with acceptable response times.

The cloud deployment enhanced accessibility, enabling users to search thesis literature from any location, thereby democratizing access to institutional knowledge resources. The system's innovative conversational approach provides a valuable tool for students and researchers, supporting informed literature discovery and academic guidance.

While promising, the system faces limitations. The dataset of 290+ theses may not fully represent disciplinary diversity, and document preprocessing quality directly impacts retrieval performance. Future research should explore scalability to larger datasets, optimization of chunk sizing and retrieval parameters, and applicability to other academic libraries. Additionally, continuous user feedback incorporation and periodic retraining with updated thesis submissions will maintain system relevance and performance.

In conclusion, this RAG-based chatbot represents a significant advancement in academic information retrieval, offering a modern alternative to traditional library systems and demonstrating the transformative potential of AI-driven semantic search in supporting academic discourse and institutional knowledge management.

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CAMARINES SUR POLYTECHNIC COLLEGES
COLLEGE of COMPUTER STUDIES

CURRICULUM VITAE

Divino Franco Rocamora Aurellano

Bicol, PH +639703880946 aurellanodivinofranco@gmail.com GitHub LinkedIn

PROFILE

I am actively studying and working on projects related to full-stack development, cloud computing, and AI. I am passionate about leveraging technology to create impactful solutions and continually strive to expand my knowledge and expertise.

TECHNICAL SKILLS

HTML/CSS/JAVASCRIPT | GIT/GITHUB | MYSQL/SQLITE/MARIADB/ | Bootstrap5 | Wordpress | Python | Retrieval Augmented Generation | Java | Flask | Django | Streamlit | Vercel

ADVANCED SKILLS

- Project Management
- Artificial Intelligence
- Cloud AI Integration
- Design Thinking
- DevOps
- Generative AI
- Cybersecurity
- Data Analysis and Visualization
- Machine Learning
- UI/UX
- Web Development
- Prompt Engineering

EDUCATION

BS Computer Science, *Camarines Sur Polytechnic Colleges* 08/2022 – 07/2026 | Bicol, Philippines
GWA: 1.3 (Consistent Dean's Lister)
Thesis: "Beyond LLMs: A RAG Chatbot for Efficient Literature Search and Thesis Retrieval in CSPC Library"
-Leading the development of a RAG-based semantic search system to revolutionize thesis retrieval and research access in our campus library.

LEADERSHIP & ACTIVITIES

Hosted Artificial Intelligence & Machine Learning (Webinar) 07/2025 | CSPC
Initiated and led a simple webinar introducing incoming sophomore students to the foundational concepts in Artificial Intelligence and Machine Learning.

Hosted Opportunities/for-Students-in- Tech-2025 (Webinar) 06/2025 | CSPC
Initiated a webinar to share the opportunities I've discovered beyond our campus. Like many institutions in underserved regions, our campus faces challenges accessing free learning resources, as tech events rarely reach us.

CERTIFICATES

- Microsoft Certified: Azure AI Fundamentals
- Github Copilot
- Github Foundations
- GitHub Administration
- Microsoft Certified: Azure Fundamentals
- Oracle Cloud Infrastructure 2025 Certified Generative AI Professional

LANGUAGES

- English — Proficient
- Bikol -Native
- Filipino -Fluent
- Spanish -Basic

AWARDS

1st Runner-Up at the Quantum Computing and Blockchain Hackathon 2025, *Quantum Computing Society of the Philippines* 19/06/2025

2025 Gawad Likha CSPCEANS, *Camarines Sur Polytechnic Colleges* 30/04/2025
Entry1: "Beyond LLMS: A RAG Chatbot For Efficient Literature Search and Thesis Retrieval in CSPC Library"
Entry2: "Optimizing Breast Cancer Diagnosis in the Philippines using SVM: A Cost-Effective Method"

1st Runner Up Impromptu Speaking - CCS Intramurals 2024, 17/08/2024
Camarines Sur Polytechnic Colleges

Herald Carl Nicol Avila

Bicol, PH +639993939533 heraldcarlavila@gmail.com GitHub LinkedIn

PROFILE

I'm a fourth-year student actively studying and working on projects in Python, AI, and full-stack development, including our capstone thesis assistant chatbot for thesis retrieval. I'm passionate about enhancing my skills in AI development, secure coding, and collaboration.

TECHNICAL SKILLS

PYTHON • HTML/CSS/JAVASCRIPT • GIT/GITHUB • MYSQL/SQLITE/MARIADB • Flask • Jupyter Notebook • Streamlit • Data Handling & Analysis • Java • Software Development

ADVANCED SKILLS

- Artificial Intelligence
- Machine Learning
- Large Language Models
- Generative AI
- Prompt Engineering
- RAG
- Natural Language Processing
- Chatbots
- Cloud AI Integration
- Web Development
- Cybersecurity
- AI Ethics & Data Privacy

EDUCATION

BS Computer Science, *Camarines Sur Polytechnic Colleges* 08/2022 – 07/2026 | Bicol, Philippines
GWA: 1.5
Thesis: "Beyond LLMs: A RAG Chatbot for Efficient Literature Search and Thesis Retrieval in CSPC Library"
- Contributing to the development of a RAG-based semantic search system to improve thesis retrieval and research access in our campus library

LEADERSHIP & ACTIVITIES

Co-hosted Opportunities/for-Students-in- Tech-2025 (Webinar)
I co-hosted a webinar to share opportunities in tech beyond our campus, helping address the challenges underserved institutions face in accessing free learning resources.

CERTIFICATES

- GitHub Foundations
- GitHub Copilot
- Cisco: Data Science Essentials with Python
- Cisco: Data Analytics Essentials
- Cisco: Intro to Cybersecurity
- IBM: AI Fundamentals with Capstone
- OCI AI Foundations Associate '25
- OCI Generative AI Professional '25

LANGUAGES

English ●●●○○ Bikol ●●●●●
Filipino ●●●●○

AWARDS

2025 Gawad Likha CSPCEANS, 30/04/2025
Camarines Sur Polytechnic Colleges
Entry: "Beyond LLMS: A RAG Chatbot For Efficient Literature Search and Thesis Retrieval in CSPC Library"

ALMIRA CALINGACION

CONTACT INFORMATION

Phone: +63 994 325 6995
Email: almiralibrando14@gmail.com
Address: Sta. Justina, Buhi, Camarines Sur
Github: https://github.com/Almira2303

PROFESSIONAL EXPERIENCE

Freelance Graphic Designer | 2023–2024
Self-Employed Graphic Designer

- Designed graphics and presentations for teachers during webinars, enhancing their teaching effectiveness.
- Collaborated with clients to understand specific design needs, ensuring satisfaction and quality.
- Managed client relationships, maintaining communication and meeting deadlines without compromise.

Part-Time Cook | 2025–Present
FriendZone Café

- Prepared and cooked menu items efficiently during peak hours, maintaining high-quality standards.
- Maintained cleanliness and organization in the kitchen, fostering a safe working environment.
- Followed food safety standards diligently, ensuring proper handling and storage of ingredients.

EDUCATION

Camarines Sur Polytechnic Colleges | 2022–2026
Bachelor of Science in Computer Science

- Dean's List Honoree

AMA Computer Learning Center | 2020–2022
STEM Track Completion

- With Honors List

LANGUAGE

Tagalog

English

TECHNICAL SKILLS

Graphic Design Fundamentals

Python Programming Basics

HTML/CSS/JAVASCRIPT

GIT/GITHUB