LLM-Based NTU Course Recommendation System

Hello, I am CourseGenie, your personal academic companion.

LIM KE EN

9 MAY 2025

Contents

Introduction

Personalised learning and recommendation systems have become the focal point for many academic institutions.

With the advent of Artificial Intelligence tools:

OpenAI, ChatGPT

Microsoft Copilot


THE STRAITS TIMES SINGAPORE

MOE prepares students for fast-changing world through tech, updating learning spaces

Showing strong potential in developing a Personalised AI Assistant

Importance of Course Selection

Degree Requirement and Academic Performance

Align with students' desired career pathways

Acquire relevant skills and knowledge

However,

IN CCDS

179

COURSES

IN CCDS

13

DEGREES

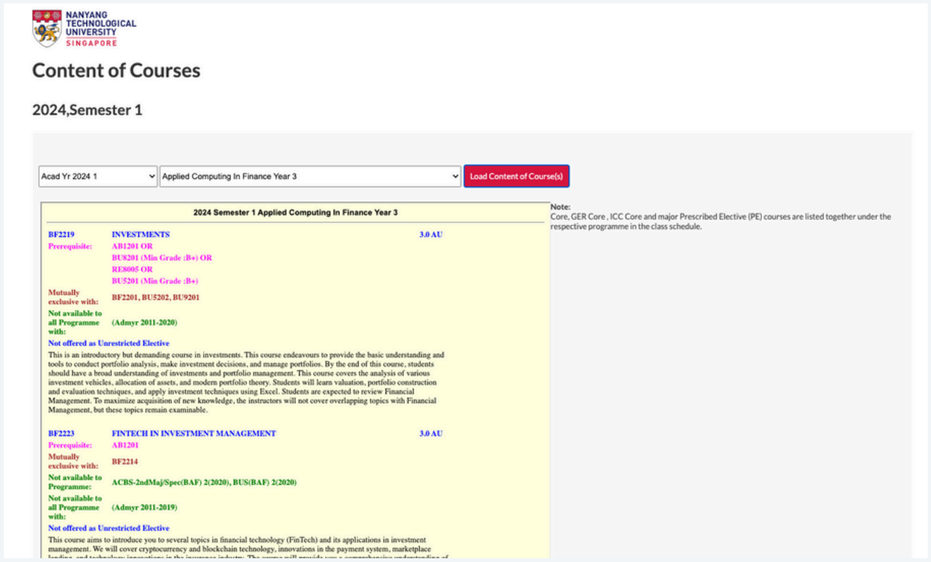
IN CCDS

12

SPECIALISATION TRACKS

Current Situation

Traditional Courses Planning Methods



NANYANG TECHNOLOGICAL UNIVERSITY SINGAPORE

Content of Courses

2024,Semester 1

Acad Yr 2024 1 | Applied Computing In Finance Year 3 | Load Content of Course(s)

2024 Semester 1 Applied Computing In Finance Year 3

BF2219 INVESTMENTS 3.0 AU

Prerequisite: AB1201 OR BUS201 (Min Grade :B+) OR RE3005 OR BU5201 (Min Grade :B+)

Mutually exclusive with: BF2201, BU5202, BU9201

Not available to all Programme with: (Admyr 2011-2020)

Not offered as Unrestricted Elective

This is an introductory but demanding course in investments. This course endeavours to provide the basic understanding and tools to conduct portfolio analysis, make investment decisions, and manage portfolios. By the end of this course, students should have a broad understanding of investments and portfolio management. This course covers the analysis of various investment vehicles, allocation of assets, and modern portfolio theory. Students will learn valuation, portfolio construction and evaluation techniques, and apply investment techniques using Excel. Students are expected to review Financial Management. To maximize acquisition of new knowledge, the instructors will not cover overlapping topics with Financial Management, but these topics remain examinable.

BF2223 FINTECH IN INVESTMENT MANAGEMENT 3.0 AU

Prerequisite: AB1201

Mutually exclusive with: BF2214

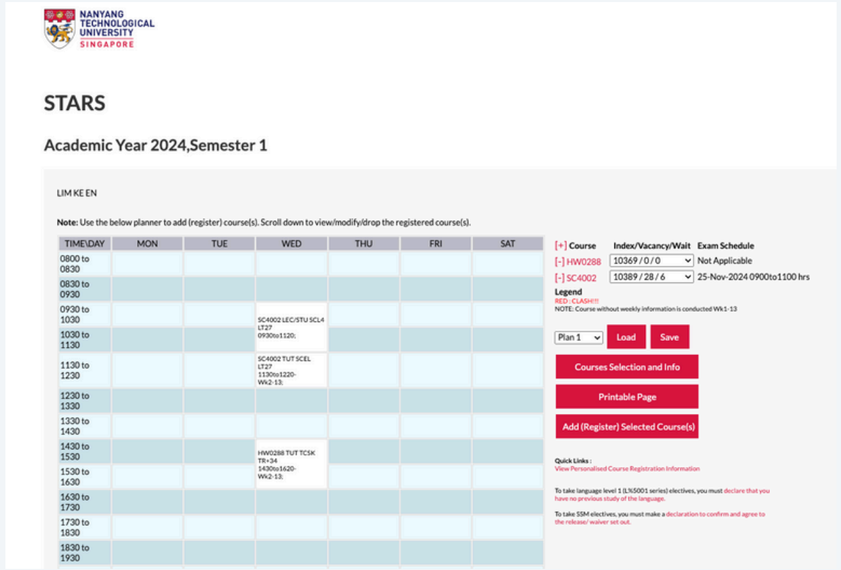
Not available to Programme: ACBS-2ndMaj/Spec(BAF) 2(2020), BUS(BAF) 2(2020)

Not available to all Programme with: (Admyr 2011-2019)

Not offered as Unrestricted Elective

This course aims to introduce you to several topics in financial technology (FinTech) and its applications in investment management. We will cover cryptocurrency and blockchain technology, innovations in the payment system, marketplace

Note: Core, GER Core , ICC Core and major Prescribed Elective (PE) courses are listed together under the respective programme in the class schedule.



NANYANG TECHNOLOGICAL UNIVERSITY SINGAPORE

STARS

Academic Year 2024,Semester 1

LIM KE EN

Note: Use the below planner to add (register) course(s). Scroll down to view/modify/drop the registered course(s).

TIME\DAY	MON	TUE	WED	THU	FRI	SAT
0800 to 0830						
0830 to 0930						
0930 to 1030			SC4002 LEC/STU SCL4 LT27 0930to1120;			
1030 to 1130						
1130 to 1230			SC4002 TUT SCEL LT27 1130to1220- Wk2-13;			
1230 to 1330						
1330 to 1430						
1430 to 1530			HW0288 TUT TCSK TR-34 1430to1620- Wk2-13;			
1530 to 1630						
1630 to 1730						
1730 to 1830						
1830 to 1930						

[+] Course | Index/Vacancy/Wait | Exam Schedule

[-] HW0288 | 10369 / 0 / 0 | Not Applicable

[-] SC4002 | 10389 / 28 / 6 | 25-Nov-2024 0900to1100 hrs

Legend

RED : CLASH!!!

NOTE: Course without weekly information is conducted Wk1-13

Plan 1 | Load | Save

Courses Selection and Info

Printable Page

Add (Register) Selected Course(s)

Quick Links :

View Personalised Course Registration Information

To take language level 1 (LN,5001 series) electives, you must declare that you have no previous study of the language.

To take SSM electives, you must make a declaration to confirm and agree to the release/ waiver set out.

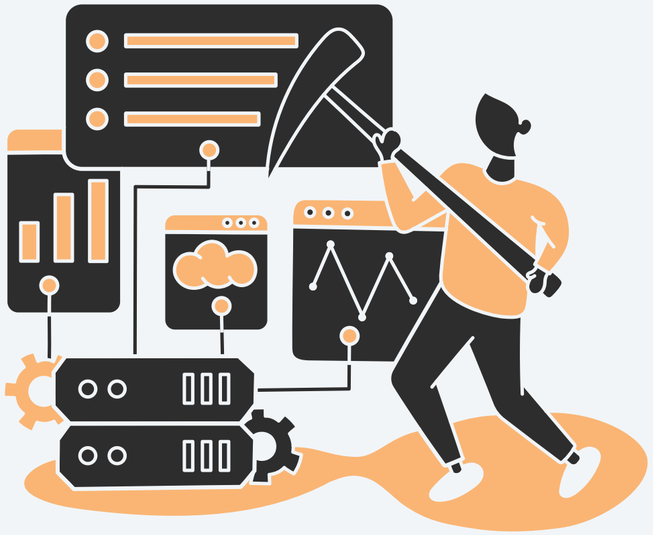
Areas of Elective Focus	Semester Offered		AU	Pre-requisite*
ARTIFICAL INTELLIGENCE	**S1**	**S2**		
SC3000 Artificial Intelligence	√	√	3	SC1007 & SC1015 & SC2000
SC4000 Machine Learning	√	√	3	SC1004 & SC1007 & SC2000
SC4001 Neural Networks & Deep Learning	√	√	3	SC1004 & SC1007 & SC2000
SC4002 Natural Language Processing	√		3	SC2001
SC4003 Intelligent Agents		√	3	SC1007 & SC2000
SC4061 Computer Vision	√		3	Nil
SC4172 Internet of Things: Tiny Machine Learning		√	3	SC2107
SECURITY	**S1**	**S2**	**AU**	**Pre-requisite***
SC3010 Computer Security	√	√	3	SC2005
SC4010 Applied Cryptography	√		3	SC2000 & MH1812
SC4011 Security Management	√		3	SC2006
SC4012 Software Security		√	3	SC2002 & SC2005 & SC2006
SC4013 Application Security	√(New)		3	SC2008 & SC2005

[School Intranet Course Website](#) to obtain information related to all the courses

NTU STARS

MPE For AY21/22 and later Cohort

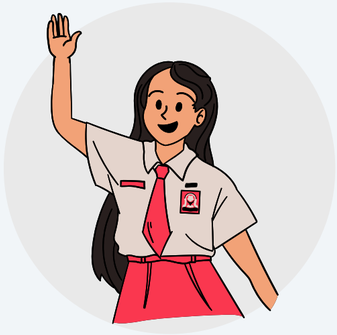
Therefore, lacking the intelligence needed to offer personalised, context-aware recommendations that align with individual academic motivations.



2. User Research

To further exemplify the current problem and understanding the needs of students, an extended user research was done and consolidated based on 3 unique personas.

USER PERSONA - MEET ALICE



NAME Alice

AGE 18

GENDER Female

ROLE JC/Poly recent graduate (Prospective NTU CCDS Student)

PROFILE	A recent graduate from Junior College and is currently applying to NTU. After shortlisting a few degree programmes, Computer Science was one of her choices. However, she is uncertain about the course curriclum and the course structure.

PAIN POINTS	**Time-consuming and tedious** in compiling all information, making her **second-guessing her choice and resulting in unnecessary stress**	**GOALS**	A clear understanding of the course structure, guidance to choose modules that fit her interests and goals, and a tool that can consolidate all of these information in one place.

USER PERSONA - MEET JOHN

NAME John

AGE 20

GENDER Male

ROLE Freshman at NTU

PROFILE

John have just began his university journey as a freshman in Computer Engineering. John is detail-oriented, but tends to overthink. He thrives in structured environment and prefers clear guidance when tackling unfamiliar tasks.

PAIN POINTS

Overwhelmed by the number of course options available and struggles to figure out how to **balance his workload**. The complexity of course-prerequisites have further elevated the stress.

GOALS

Wants to excel academically and build a solid, well-planned academic path for all four years. He **values clarity** and wants to feel in **control of his academic journey from the very start.**

USER PERSONA - MEET GRACE

NAME Grace

AGE 23

GENDER Female

ROLE Penultimate student in NTU

PROFILE

A penultimate-year student majoring in Computer Science at NTU. She has completed most of her Core courses, and it's now time to choose her Major Prescribed Electives, or MPEs.

PAIN POINTS

The sheer number of elective options has **left her feeling paralysed by choice**. She is unsure which courses actually **give her a competitive edge in her chosen career path and interests**.

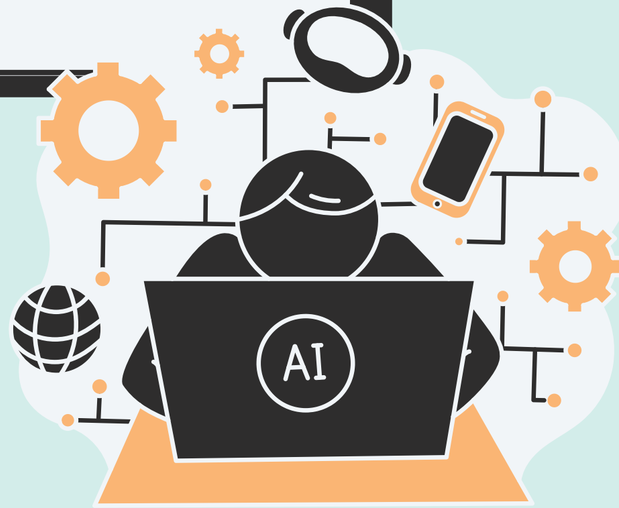
GOALS

Wants to choose electives that **play to her academic strengths** so that she can **maintain her strong GPA,** as well as closely **aligning to her career interests.**

Looking for a **smart, personalised recommendation system** that can recommend based on her interests, past performance, and future career goals.

3. Problem Statement

Current course planning methods lacks a **centralised, intuitive approach** to navigate course planning, understand prerequisites easily, and receiving personalised academic guidance. This results in **stress, inefficiency and missed opportunities** for optimal academic and career outcomes.



Problem Aim

Aims to bridge the gap between educational offerings and students' academic motivations.

Streamline Course Research

Introduces an information retrieval that can reduce the time students spend searching for information on CCDS Course Curriculum

Deliver Personalised Recommendations

To generate real-time personalised course recommendations that align with individual academic goals and interests

Ensure High Precision and Accuracy

Provide precise and contextually relevant responses that leverages Retrieval Augmented Generation (RAG) techniques to deliver accurate responses.

Enhance User Engagement

Develop an intuitive, conversational interface that simplifies course research procedures.

Key Features

01

Course Information Retrieval via Chatbot

To interact with the chatbot to ask questions about specific courses, to retrieve information about courses in CCDS easily

02

Personalised Course Recommendations

To receive personalised course recommendations that closely align with students' interests and academic performance to make well-informed decisions throughout their university journey

03

Profile Creation

Enable profile creation to provide unique information such as academic background, interests and career aspiration to provide recommendations tailored to students' educational needs and goals.

04

Upload Degree Audit

Easily provide information from degree audit to easily provide the system with student's course grades

05

Visual Roadmap of Academic Plan

Visualised a course roadmap to easily understand the progression and structure of user's academic plan

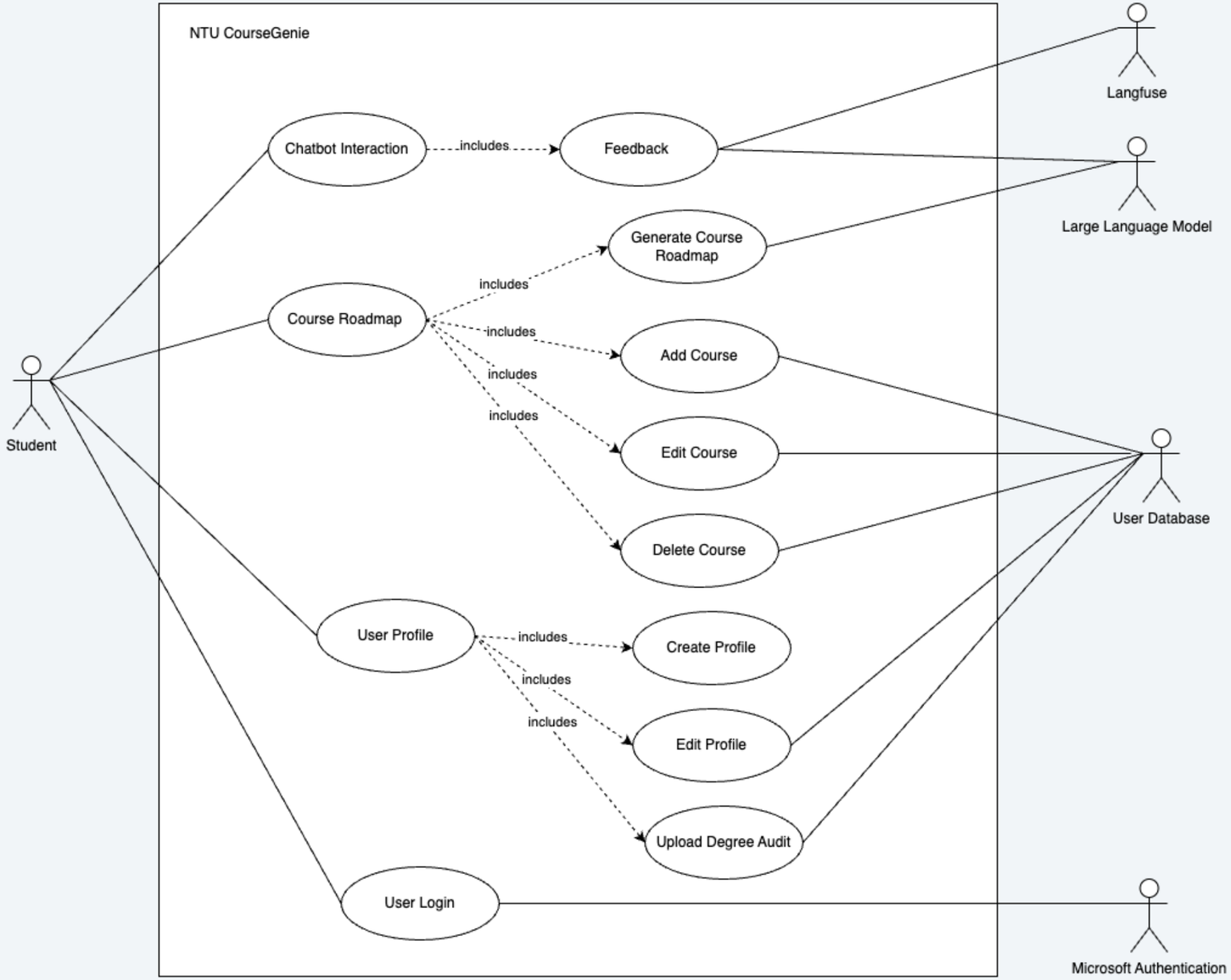
06

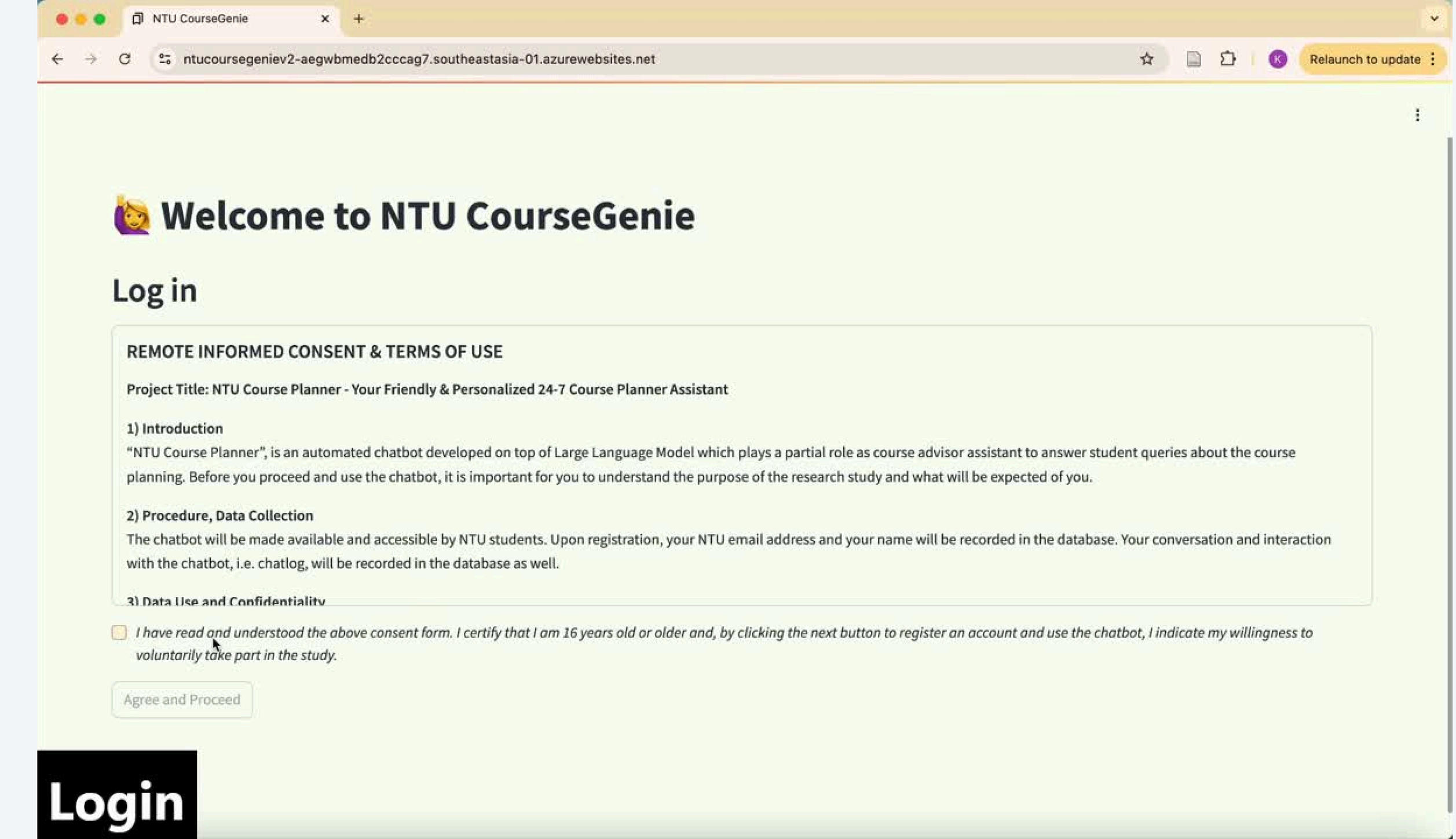
Interactive Academic Roadmap

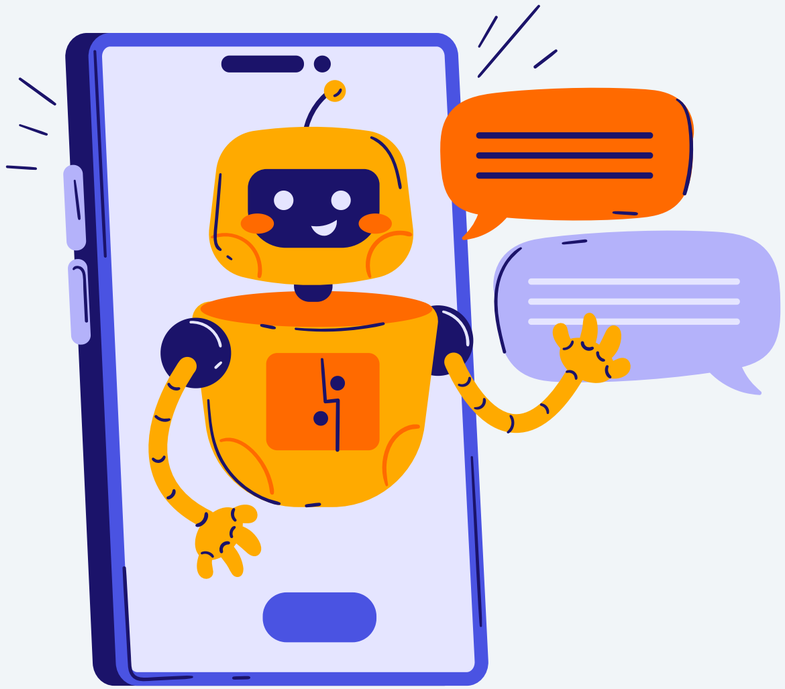
Dynamically add, delete or edit courses to easily personalise the roadmap to suit users' needs and preferences

4. Use Case Diagram

Outlines the key features of NTU CourseGenie




NTU CourseGenie
ntucoursegeniev2-aegwbmedb2cccag7.southeastasia-01.azurewebsites.net
Relaunch to update
Welcome to NTU CourseGenie
Log in
REMOTE INFORMED CONSENT & TERMS OF USE
Project Title: NTU Course Planner - Your Friendly & Personalized 24-7 Course Planner Assistant
1) Introduction
"NTU Course Planner", is an automated chatbot developed on top of Large Language Model which plays a partial role as course advisor assistant to answer student queries about the course planning. Before you proceed and use the chatbot, it is important for you to understand the purpose of the research study and what will be expected of you.
2) Procedure, Data Collection
The chatbot will be made available and accessible by NTU students. Upon registration, your NTU email address and your name will be recorded in the database. Your conversation and interaction with the chatbot, i.e. chatlog, will be recorded in the database as well.
3) Data Use and Confidentiality
I have read and understood the above consent form. I certify that I am 16 years old or older and, by clicking the next button to register an account and use the chatbot, I indicate my willingness to voluntarily take part in the study.
Agree and Proceed
Login



5. Chatbot Design Consideration

Enhancing Course Planning with LLMs: A Multi-Agent RAG-Based Recommendation Framework

Chatbot Design Considerations

Rely on retrieval techniques and in-context learning to provide explainable and personalised recommendation

1. Limitations of LLMs
2. Agentic Workflow
3. Explanation of Agents

Limitations of LLMs

While LLMs today offers promising reasoning capabilities that can understand context, generate human-like text and perform complex reasoning to facilitate a more engaging and intuitive user interactions.

However, despite that, LLMs today still succumbs to hallucinations due to:

Do not contain updated information

LLM's knowledge have a cut-off date - GPT-4o is only trained till Oct 2023

Deficit in domain specific knowledge

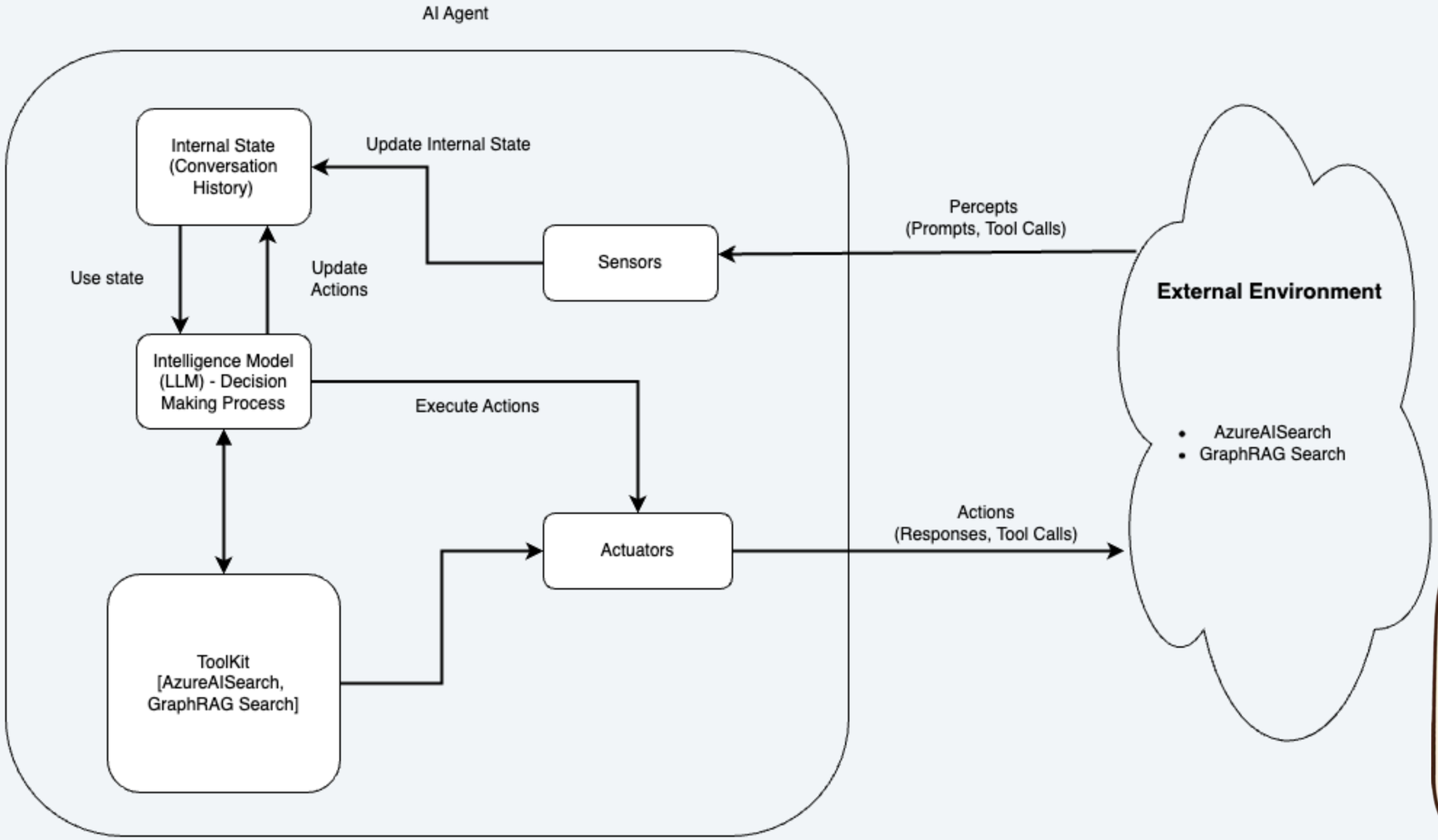
Lack of specific knowledge such as the course details in NTU CCDS

Therefore, to build a reliable AI application that incorporates domain-specific data, such as specific course information, data augmentation techniques like Retrieval Augmented Generation (RAG) frameworks are proposed.

Information Retrieval Pipeline for Chatbot

Agentic Workflow

- By definition, an agent is anything capable of perceiving its environment through its sensors and interacting with the environment through the actuators

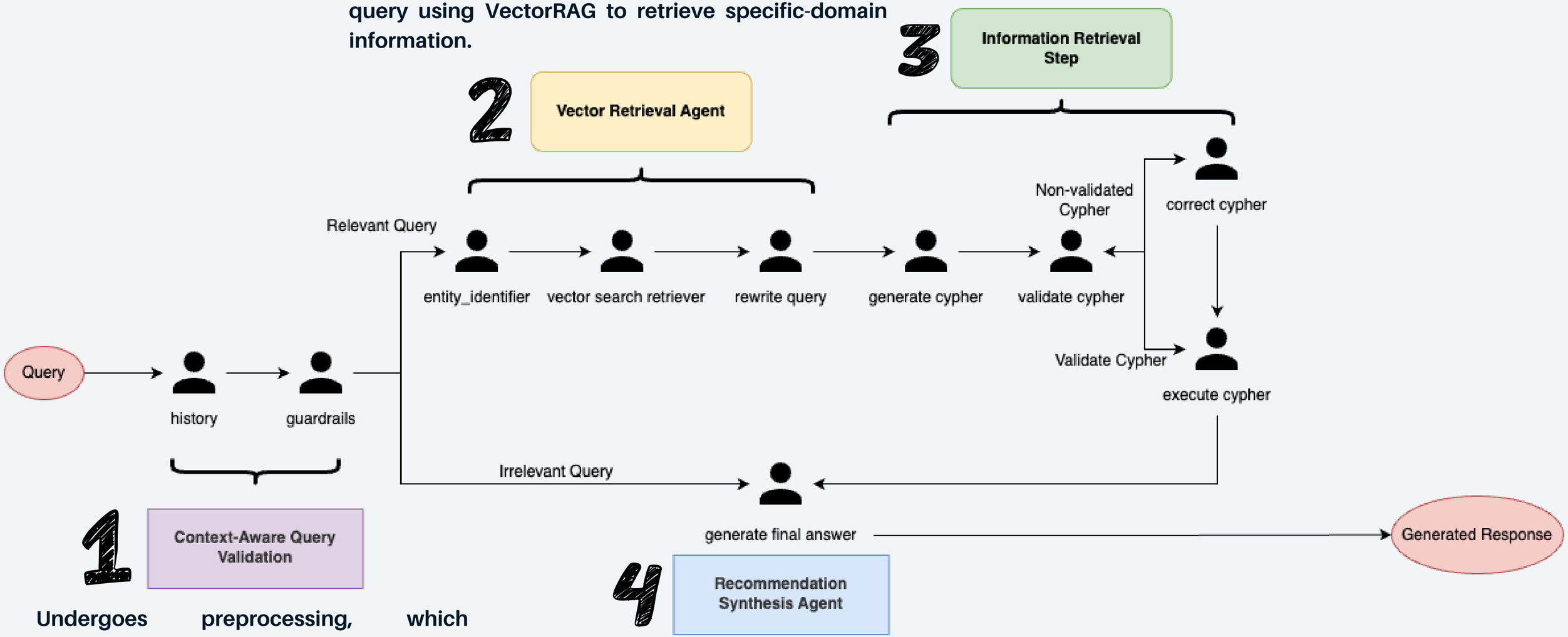


The outcome of these actions can create new perceptual inputs, reinforcing the iterative nature of the agent's workflow.

Overall Agent Workflow

Enriched queries are then processed using GraphRAG, a graph-based reasoning framework that extracts relational data specific to courses.

Semantic similarity analysis is performed on refined query using VectorRAG to retrieve specific-domain information.



Undergoes preprocessing, which integrates conversational history for contextualisation and applies guardrails to ensure query relevancy.

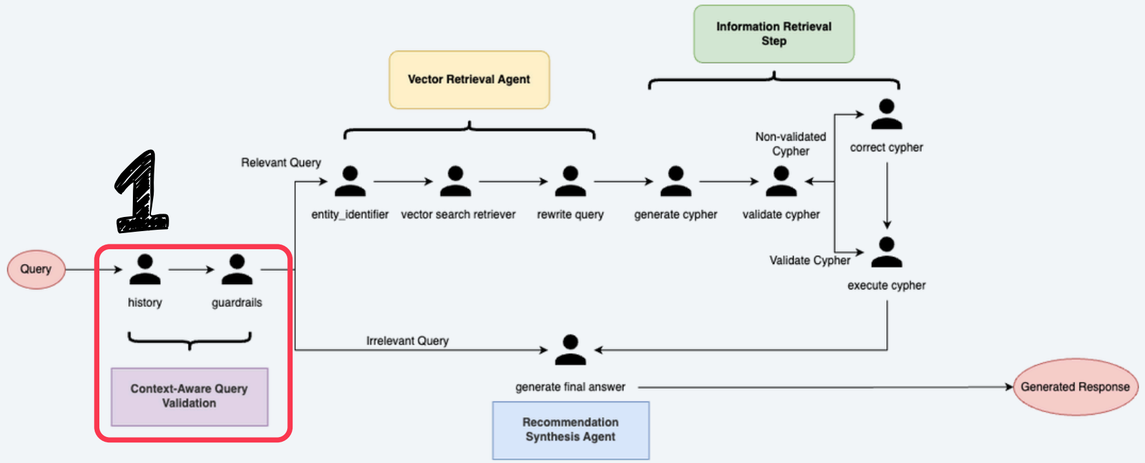
All relevant information are conslidated by the final answer generator agent, which synthesises a response.

1 Context-Aware Query Validation

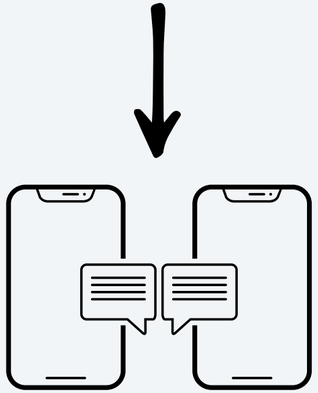
A dialogue system was designed to leverage both conversational history and user profiles.

By employing Chain-of-Thought prompting technique, the system harnesses the capability of LLM to comprehend previous conversations and to contextualise entities within the query.

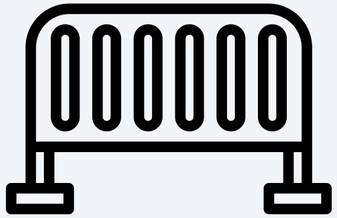
Query undergo a validation process to assess its relevance to course planning and effectively filter out any unrelated queries.



Query

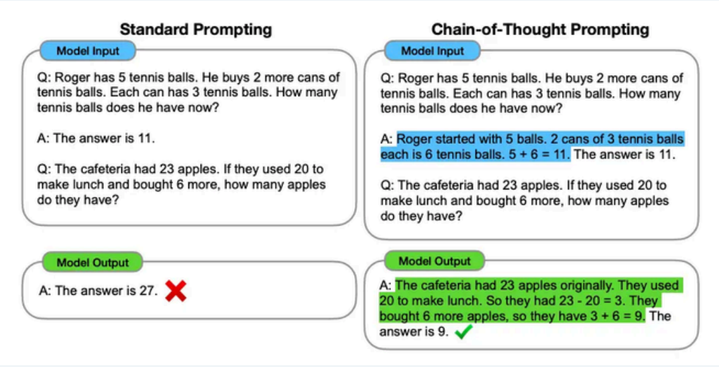


Conversational History



Guardrails

Chain-of-Thought Prompting



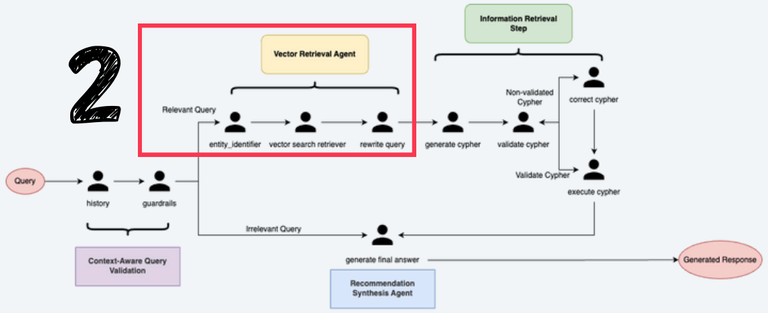
- Detect and block irrelevant query
- Detect and block jailbreak attempts

2 Query Preprocessing

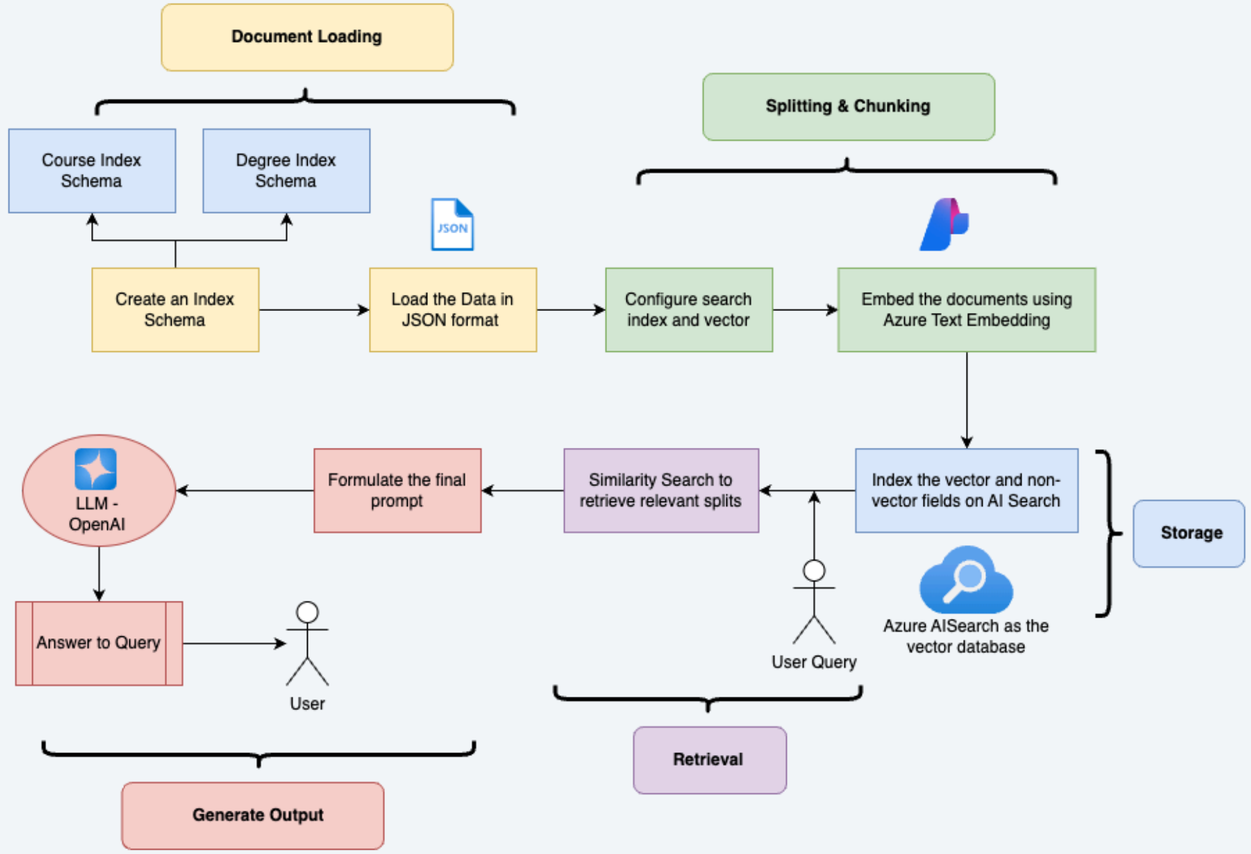
User queries are ambiguous, which may lead to misinterpretation and increase the risk of hallucination by LLMs.

Named entities needs to be extracted from the query to clarify the user's intent.

System employs VectorRAG - that integrates vector embeddings to enhance domain-specific context.



- **Indexing**
  - **Documents in JSON formats are pre-processed, embedded using embedding models, and indexed into Vector Database (AzureAISearch) as the knowledge base.**

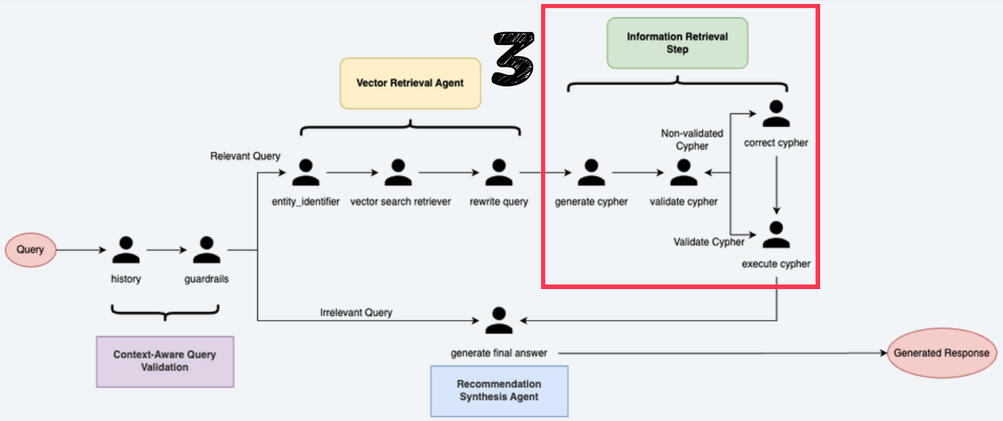


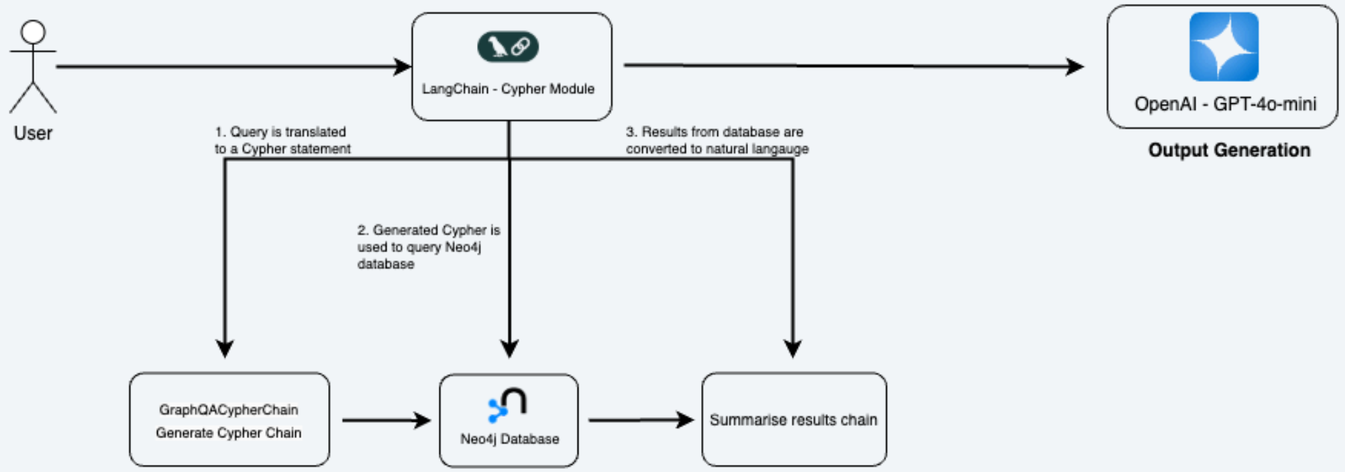
- **Retrieval Phase**
  - **Extracted entities are vectorised and semantic similarity search are performed.**
  - **Relevant document chunks are appended to the system prompt, forming accurate responses.**

3 Information Retrieval

To retrieve relevant information, we employ a step-by-step agentic approach, where LLMs convert user queries into Cypher (a graph query language) along with few-shot prompting.

These queries are validated and executed on the knowledge graph to retrieve relevant, structured data for generating coherent responses.





Knowledge graphs enhance interpretability by retaining intricate relationships, allowing LLMs to reason more effectively.

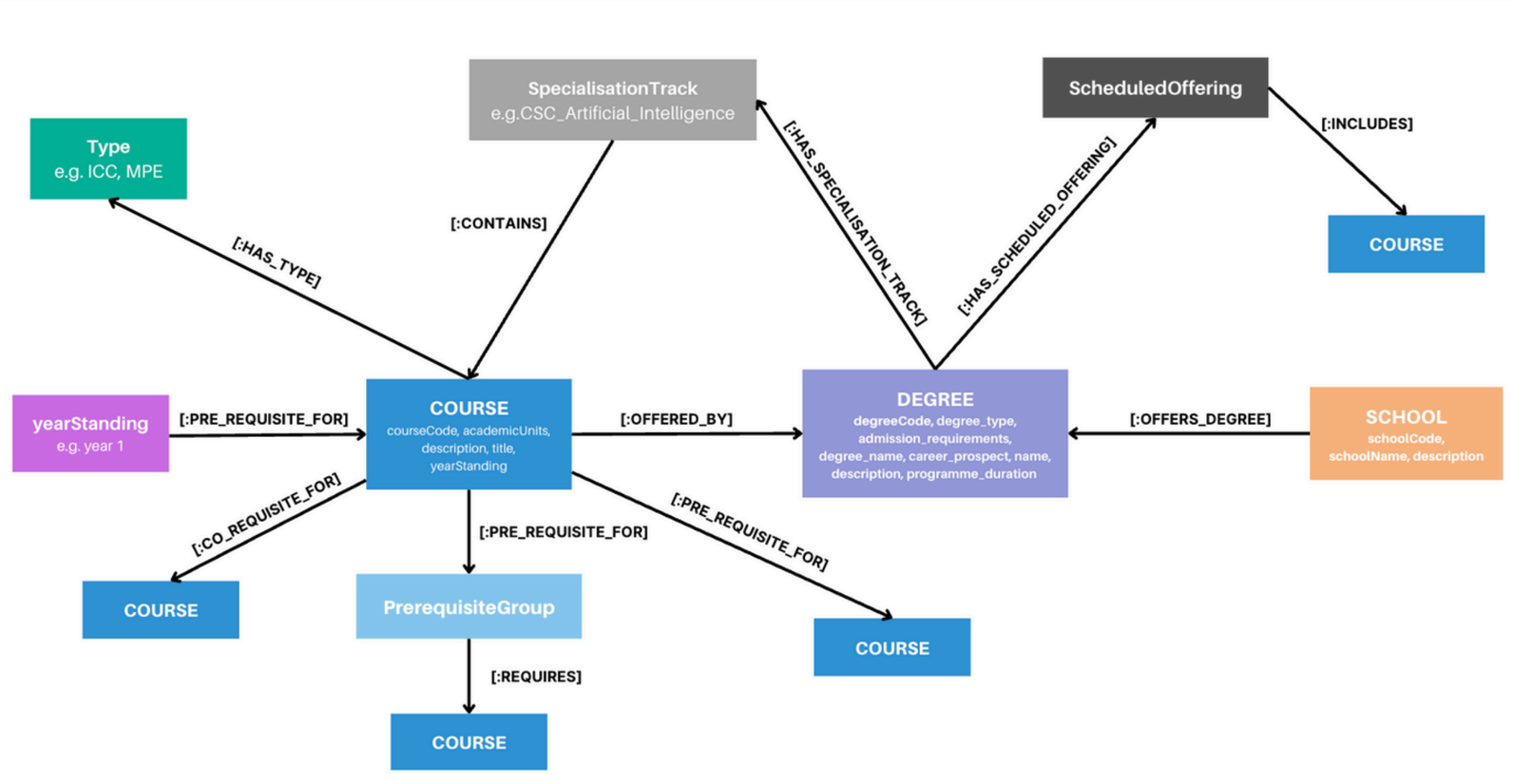
GraphRAG Approach - Knowledge Graph Creation

A knowledge graph is a graphical representation of data that model data as interconnected nodes (entities) and edges (relationships), preserving complex relationships and attributes.

- Compared to storing data in simple semi-structured data forms, such as CSV or JSON, which may result in the loss of contextual relationships between data, the use of knowledge graphs effectively mitigates these limitations.

Benefits

Provides greater flexibility to surface hidden patterns through relationships within the data, enabling LLMs to easily comprehend complex relationships between entities.



VectorRAG VS GraphRAG

Feature/Aspect	VectorRAG	GraphRAG
Stored data structure	Relies on vector embeddings	Utilises a knowledge graph (e.g. Neo4j) where nodes and edges represents entities and relationships in a structured manner
Retrieval Mechanism	Using distance metrics such as Euclidean distance or performing of similarity search	Relies on Cypher query language to extract nodes and relationships from graph
Data Type suitability	Ideal for unstructured or semi-structured textual data	Suited for structured or semi-structured data when the relationships between data is crucial
Level of explainability	Retrieved information is based on semantic similarity, lacking in the level of explainability	Structured nature of knowledge graph allows for more interpretable reasoning, increasing accuracy
Complex reasoning	Unable to perform multi-hop reasoning between disparate data points	Excels at multi-hop reasoning, can traverse through connected relationships between pieces of information

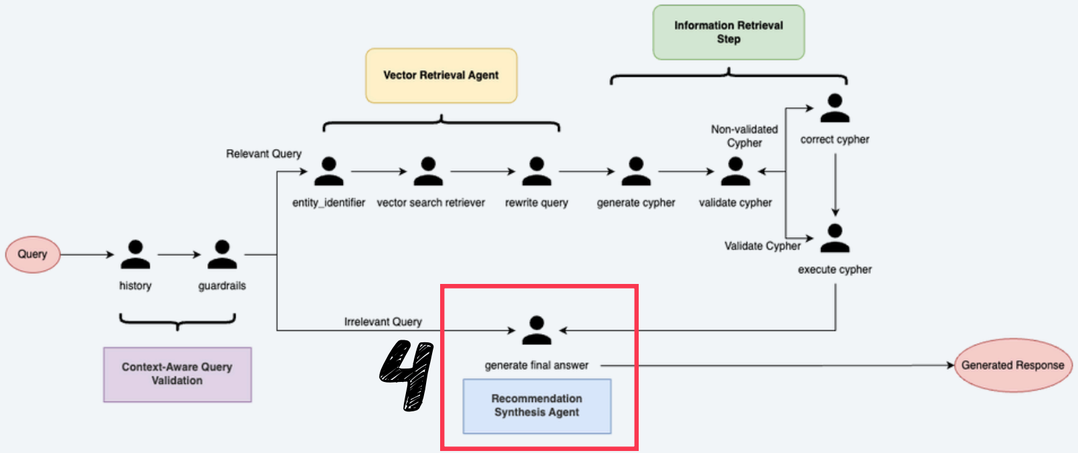
GraphRAG is better at identifying intricate patterns, leading to more grounded and accurate outputs, particularly in recognising prerequisite chains and hierarchical course structures. → Main Information Retrieval Method

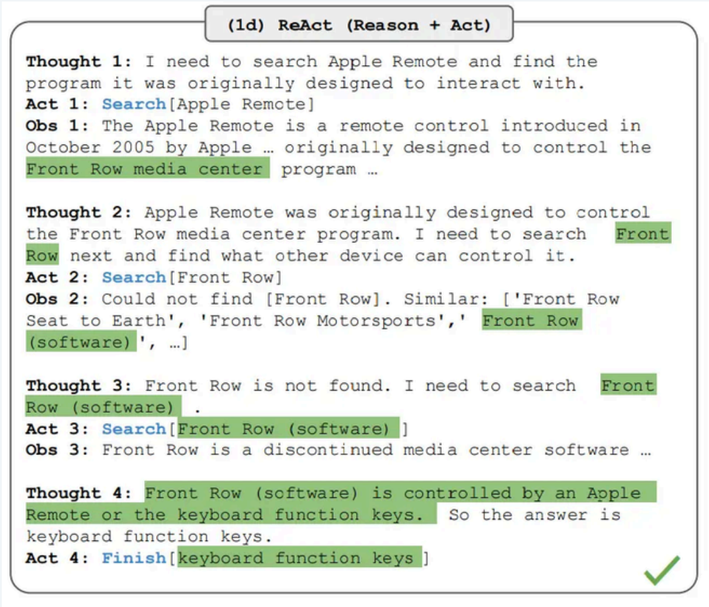
4 Recommendation Generation Synthesis

ReAct prompting a prompting technique that combines both reasoning and action with LLM is integrated.

By appending the retrieved context to the system prompt, a long contextual input is formed.

Agent will reason based on the query and retrieved context to generate a coherent response.





6. Preliminary Evaluation

Performing evaluation of NTU CourseGenie

6. Preliminary Evaluation

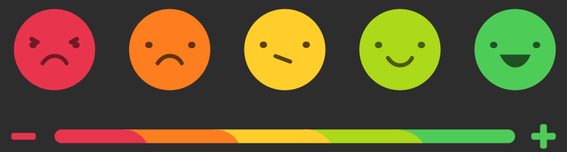
Evaluating conversational course recommendation systems presents significant challenges through a mass online survey, feedback through natural and open-ended dialogues and a Quantitative LLM Evaluation.

1. Mass Online Survey

Dedicated feedback form was created and embedded the form within the website, to easily reach a broader and diverse group of testers, gaining compreensive feedback.

2. Production Testing

Three undergraduate students were invited to participate in a one- hour live testing session to interact with the recommendation system prototype and provide feedback.



3. Qualitative LLM Evaluation

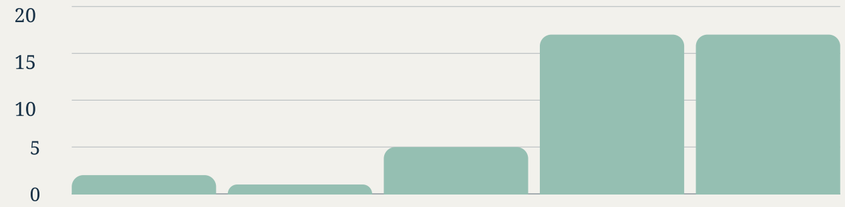
To further evaluate the performance of the multi-agent pipeline, raw user queries were collected and assessed using RAGAS framework.

6. Preliminary Evaluation

1. Mass Online Survey

To better understand user sentiments regarding NTU CourseGenie's features and functionality, a feedback form was developed. The form included a mix of short-answer and rating-scale questions to ensure a quick and user-friendly experience.

A total of **42 responses** were collected, primarily from first- and second-year CCDS students. The survey aimed to evaluate both the effectiveness of existing course planning methods and the overall user experience with NTU CourseGenie.



Average Rating of 4.17

for the accuracy of the chatbot responses

4.14/5 average overall user experience score

Users indicate a relatively high user experience score

4.14/5

★★★★☆

80% Users satisfaction

Users are satisfied as NTU CourseGenie helps in addressing their pain points.

15%

15% increase in productivity

Survey results indicates that users found NTU CourseGenie both useful and effective, with majority of respondent rating it between 4 and 5.

Highlights the value it brings to students and emphasises its strong potential for further development and enhancement.

2. Production Testing

Three undergraduate students were invited to participate in a one-hour live testing session to interact with the recommendation system prototype and provide feedback.

During the session, students were first asked to reflect on their course planning journey and were provided with specific instructions to interact with the recommendation system.

They were encouraged to verbalise their thought process and reasoning throughout the interaction. This approach helps uncover users' mental model and facilitated the collection of qualitative user feedback.

Key features that were well-received:

A – Course Information retrieval	
Current Method	Students manually search for course information across different sources
Pain Points	Information is scattered and time-consuming to consolidate, difficult to access all course details efficiently
Features	Centralized, one-stop platform to access comprehensive course information
B – Course Recommendation	
Current Method	Static course content websites used for course selection and planning
Pain Points	Lacks personalization; students struggle to align courses with their interests
Features	AI-powered dynamic recommendations based on user profiles and preferences
C – Course Mapping	
Current Method	Manually identify eligible courses
Pain Points	Prerequisites are unclear; high tendency in missing out key eligibility
Features	Intelligent mapping of eligible courses based on academic history and prerequisites

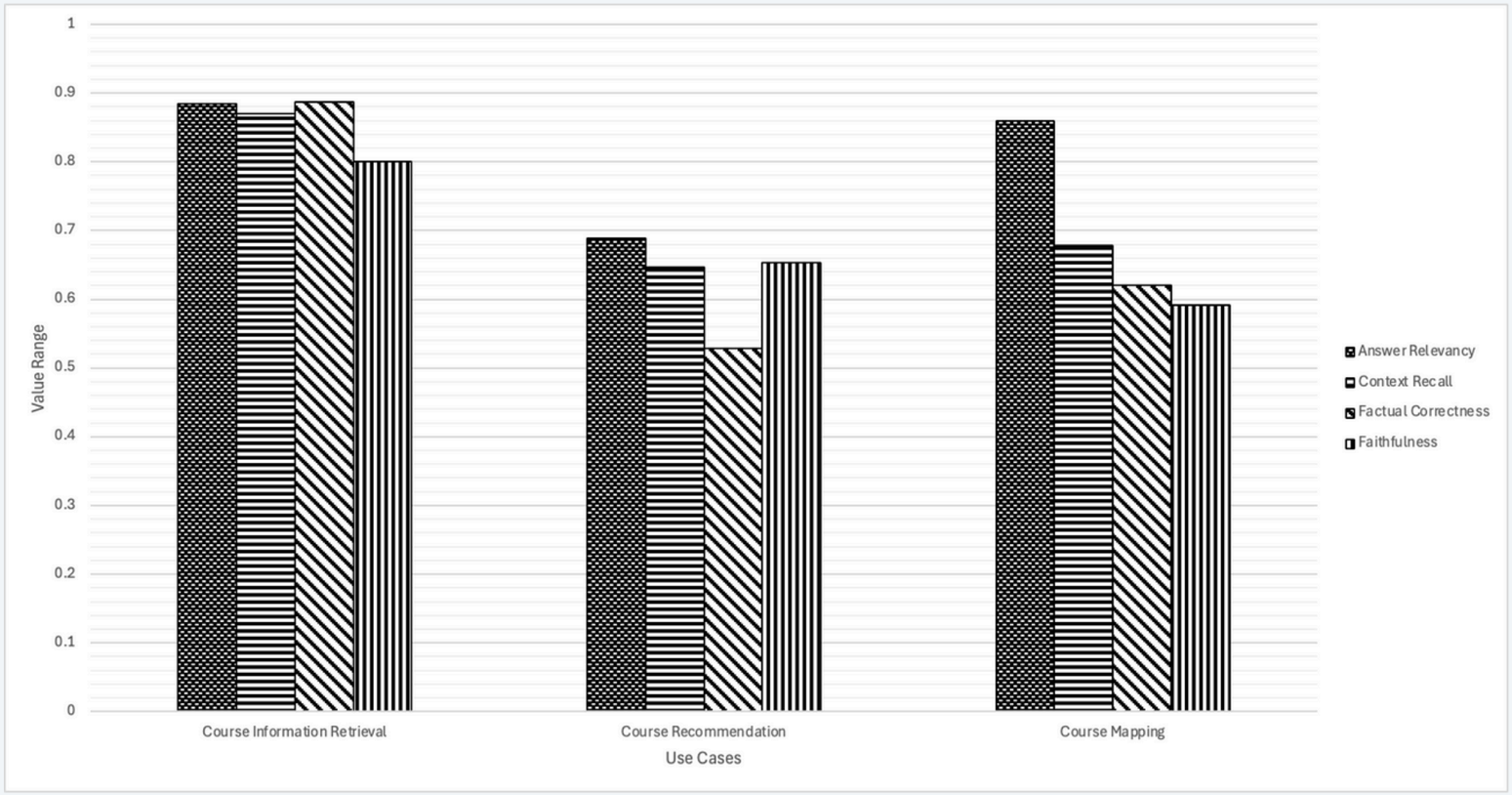
3. Qualitative LLM Evaluation

The RAGAS framework provides tools to automate the evaluation of LLM applications through a set of quantitative metrics.

These metrics offer a unified approach to measure the system's performance against test data.

By assigning a numerical value ranging between 0 to 1, this framework helps to maintain consistency and interpretability across different dimensions holistically for evaluation.

6. Preliminary Evaluation



- Occasional hallucinations and inaccuracies in the retrieved information were observed, signalling limitations in factual grounding.

- Overall, the system shows strong performance, especially in information retrieval, while occasionally provides imprecise or incomplete responses, particularly when generating recommendations or handling vague queries.

7. Conclusion

In conclusion, NTU CourseGenie serves as a one-stop solution to assist NTU CCDS students in navigating through their academic journeys in NTU. By leveraging the powerful reasoning capabilities of LLMs, NTU CourseGenie offers students comprehensive, real-time course recommendations, acting as their personal academic companion.

Achievements

Submitted a short paper to ACM Recsys 2025

Enhancing Course Planning with LLMs: A Multi-Agent RAG-Based Recommendation Framework

ABSTRACT

A dynamic course recommendation system should effectively emulate an academic advisor, personalizing guidance based on each student's strengths, weaknesses, and career interests. Given that course selection significantly influences academic performance and degree completion, the current and conventional approaches often fail to provide adequate personalization. This paper introduces an intelligent, conversational-based course recommendation system that leverages recent advancements in Generative AI. Utilizing Large Language Models (LLMs) and sophisticated Retrieval Augmented Generation (RAG) techniques along with novel integration of VectorRAG and GraphRAG within a Multi-Agentic framework. The system first analyzes student profiles and queries to retrieve contextually relevant course information. It then dynamically recommends optimal courses aligned with student objectives. A human-in-the-loop approach continuously refines the system's knowledge base by addressing knowledge gaps iteratively. Preliminary evaluation results indicate that this system significantly enhances the course planning experience, reducing the time students spend on academic planning and empowering them to navigate their educational pathways strategically.

KEYWORDS

Course Recommendation, Conversational Recommendation, Multi-Agent, Applied Large Language Models

Introduction

In the ever-evolving educational landscape driven by rapid technological advancements, personalized learning and recommendation systems have become critical in enhancing student experiences and outcomes [1]. The advent of LLMs, such as GPT-4, has opened new frontiers to cater for personalized learning that can generate personalized content aligned with students' interests and academic goals [2].

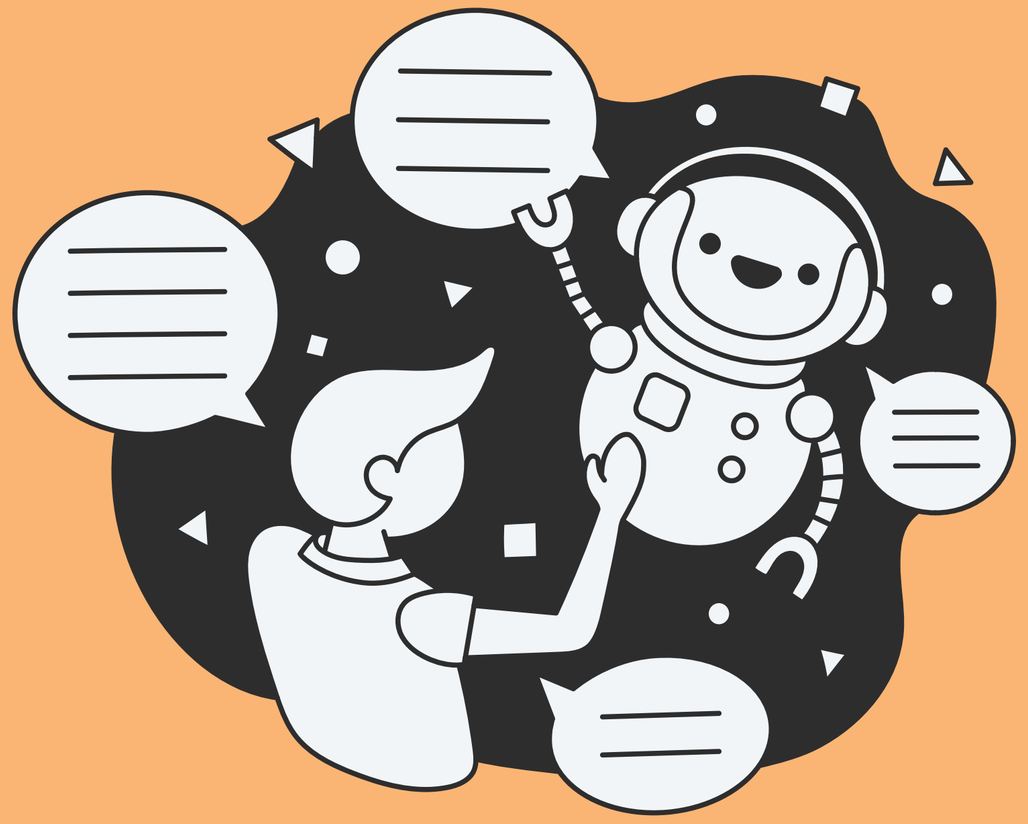
One of the most pivotal decisions that tertiary education students face is the course planning, which influences their academic trajectories and future career opportunities [3]. Unlike pre-university education, where course schedules were pre-designed, students at the university level have to bear the responsibility of planning their own schedules and choosing elective courses independently. However, given the increasing complexity of modern education systems, students are often overwhelmed by the vast amount of information and may face analysis paralysis. This makes it challenging for students to objectively evaluate which course best plays to their strengths [4]. Current course planning methods tend to be static and document-heavy, lacking the intelligence needed to offer personalized, context-aware recommendations that align with individual academic motivations. Moreover, these conventional recommendation systems or approaches often operate as black boxes, providing limited interactivity and transparency, which results in ineffective personalization in their recommendations.

In contrast, Large Language Models (LLMs) offer promising reasoning capabilities that can understand context, generate human-like text, and perform complex reasoning tasks to facilitate more engaging and intuitive user interactions. However, despite their potential, the model still succumbs to hallucinations due to the deficit or inadequacy in domain-specific knowledge and up-to-date information. Hence, relying on pre-trained models increases the risk of response inaccuracies from missing or outdated context [5]. To build a reliable AI application that incorporates domain-specific data, such as specific course information, data augmentation techniques like Retrieval Augmented Generation (RAG) frameworks are proposed. RAG is a powerful AI framework that grounds LLM responses with external, query-relevant knowledge source, aiming to supplement the internal knowledge of LLMs.

In this paper, we present a novel conversational course recommender system that integrates different retrieval techniques within a multi-agentic workflow. Unlike approaches that requires extensive training or fine-tuning of models, the system relies solely on retrieval techniques, in-context learning, and human-in-the-loop feedback to provide explainable and personalized recommendations. This approach aims to redefine how students engage with academic planning tools, transforming overwhelming task into an intuitive experience.

Methodologies

An agent-based workflow is designed to generate accurate and contextually relevant responses, as shown in Figure 1. Initially, the query undergoes preprocessing, which integrates conversational history for contextualization and applies guardrails to ensure query relevance. Semantic similarity analysis is performed on the refined query using VectorRAG to retrieve specific-domain information. These enriched queries are then processed using GraphRAG, a graph-based reasoning framework that extracts relational data specific to courses. For ambiguous queries classified as non-trivial, a human-in-a-loop reasoning agent is invoked, allowing for human intervention to enhance accuracy and relevancy. Finally, all the relevant information are consolidated by the final answer generator agent, which synthesizes a coherent and comprehensive response.



Thank You!

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