

# **Development and Deployment of a Chatbot for UoR**

By

Aslam Syed

Submitted to

**The University of Roehampton**

In partial fulfilment of the requirements

for the degree of

**Master of Science**

in

**Computing**

## Declaration

I hereby certify that this report constitutes my own work, that where the language of others is used, quotation marks so indicate, and that appropriate credit is given where I have used the language, ideas, expressions, or writings of others.

I declare that this report describes the original work that has not been previously presented for the award of any other degree of any other institution.

Aslam Syed

08/08/2025

A handwritten signature in black ink, appearing to read "S. Aslam".

## Acknowledgements

I would like to express my sincere gratitude to Karim Bouzoubaa for his invaluable assistance and guidance with the IBM Watson chatbot implementation. I am also thankful to Fakhreldin Saeed for his support and advice throughout the development of the Ollama-based chatbot. Their expertise and encouragement were essential in the successful completion of this project.

## Abstract

This project investigates the creation and testing of AI-powered chatbots designed for higher education, with a specific focus on increasing student interaction and access to university information. The rapid growth of artificial intelligence technologies has enabled colleges to use chatbots as effective tools for handling academic and administrative questions, increasing student happiness while reducing staff workload. A thorough analysis of the current research demonstrated the effectiveness of educational chatbots in providing timely help, personalised learning experiences, and operational efficiencies, while also emphasising the ethical concerns about data protection and transparency.

The implementation phase included the creation of two unique chatbot systems: one powered by IBM Watson and the other by leveraging Ollama's LLM combined with Langchain and a vector database for contextual information retrieval. Both chatbots were built to accurately respond to questions regarding the University of Roehampton, using domain-specific datasets to assure relevance and dependability. The IBM Watson chatbot was built around natural language understanding and pre-made conversation flows, but the Ollama-based chatbot used advanced embedding techniques and dynamic retrieval to deliver context-aware responses.

The evaluation of these systems proved their capacity to handle a wide range of student enquiries efficiently, with the Ollama chatbot providing enhanced contextual comprehension via its vector-based retrieval mechanism. However, limitations such as occasional misinterpretations and difficulties addressing confusing enquiries were noted. User response emphasised the potential of chatbots to supplement traditional student services, while emphasising the need for ongoing updates and ethical protections.

Finally, this experiment verifies the promising role of AI chatbots in higher education, demonstrating their effectiveness in speeding information access and increasing user experience. Future research should address identified flaws and ethical concerns in order to build confidence and widespread adoption.

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# Chapter 1: Introduction

In today's fast-paced digital environment, students expect quick, dependable, and personalised assistance, particularly while navigating university life. Whether it's about course registration, deadlines, or campus services, having the appropriate information at the right time can make a significant difference in a student's experience. That is where this initiative fits in. This virtual assistant is intended to answer common enquiries, walk people through university processes, and respond in a way that is not just correct but also emotionally attentive. University life can be thrilling, but it also presents its own set of challenges, such as locating the correct information, figuring out processes, and knowing who to ask for support. For many students, particularly those new to higher education or studying in various time zones, even little obstacles such as unclear deadlines or perplexing course registration procedures can rapidly become burdensome. Students are now expecting the same level of attention from their colleges in an age when we are accustomed to rapid answers and digital convenience. The increased desire for on-the-go, accessible help is altering how institutions approach communication, and conversational AI is emerging as a powerful option.

AI-powered chatbots are also becoming increasingly popular in a variety of professions, including education [8]. Businesses, hospitals, and even government organisations are using AI to improve how they engage with customers. This study takes on that trend and investigates how conversational AI may truly make life easier in a university setting.

## 1.1 Problem Description, Context and Motivation

Students, faculty, and interested candidates at the University of Roehampton (UoR), like many other higher education institutions, routinely seek information and assistance on a variety of topics, including course specifics and application deadlines, as well as campus services and academic support. Traditionally, this support has been offered by email, helpdesk enquiries, phone conversations, and in-person visits. However, these methods are frequently constrained by personnel availability, working hours, and the increasing volume of enquiries that student services teams must manage. The issue is simple but significant: students frequently encounter delays, irritation, or confusion while attempting to get critical information or support, particularly outside of regular office hours. These concerns can have a severe impact on the student experience, resulting in missed deadlines, stress, and even disengagement from academics. Staff personnel are also affected, as many spend a significant amount of time answering repetitive questions, limiting their ability to focus on more complex or important duties.

In the modern digital world, students expect faster, more personalised solutions. They are accustomed to smart assistants such as Siri, Alexa, and chatbots in online customer support [10]. However, most colleges have not fully implemented AI-powered technologies to provide round-the-clock help. The gap between student goals and the current support system is an obvious opportunity for improvement.

A direct impact on student satisfaction, enrolment, and overall academic success. A more accessible and emotionally intelligent support system can promote decision-making, well-being, and create a closer bond between students and the university [9]. Automating routine interactions sets up staff time for high-value, human-centered support and strategic work.

In simple terms, the main issue is a lack of timely, emotionally aware support for students and university users, particularly when staff are unavailable. The idea is to create an intelligent chatbot for UoR that offers real-time, sympathetic assistance, bridging the gap between human care and technological ease.

## 1.2 Objectives

The purpose of this project is to construct an intelligent, student-focused chatbot that will serve the University of Roehampton community by providing fast, informative answers to common university-related concerns. The chatbot will function as a virtual assistant, answering questions regarding admissions, course information, deadlines, student services, and campus facilities.

One of the primary goals is to increase the accessibility and responsiveness of support services. University staff are frequently met with frequent questions, which can cause delays and frustration among students. By automating common conversations, the chatbot ensures that students receive prompt responses at any time of day or night, without having to wait for office hours or email replies.

A further important objective is to improve the user experience through emotionally aware answers. By using tone detection technology, the chatbot will be able to identify emotions in a student's communication, such as tension or perplexity, and respond with empathy. This function is intended to make the contact feel more personal user experience.

In addition to the technological components, the project is committed to strong ethical and privacy principles, ensuring that user data is handled properly and in accordance with applicable regulations.

Finally, the goal of this chatbot is to create a more connected, supportive atmosphere for users, not only increase productivity. If successful, it could serve as a model for other colleges considering using emotionally intelligent computer support systems.

## 1.3 Methodology

### 1.3.1 Design

The project uses a modular design approach to create two AI-powered chatbot systems:

- **IBM Watsonx Assistant** will be utilised to conduct organised, rule-based conversations and answer frequently asked enquiries regarding the University of Roehampton (e.g., admissions, student services, campus facilities).
- **Ollama** will be used to generate and contextualise responses, facilitating open-ended questions and more natural discourse.

Conversation flows are created utilising insights from the literature study to ensure coverage of typical student questions and easy navigation. The user interface elements are designed to be accessible and responsive, allowing the chatbot to run on desktops.

### 1.3.2 Testing and Evaluation

Testing will follow an iterative cycle that includes:

- **Unit testing** ensures that each chatbot module operates as planned.
- **User Testing** - Six volunteer students will assess the chatbot's clarity, correctness, and usability.
- **Performance evaluation** involves using surveys to assess response speed, accuracy rate, and customer satisfaction. Both IBM Watsonx and Ollama results will be compared to see whether one performs better for various query types.

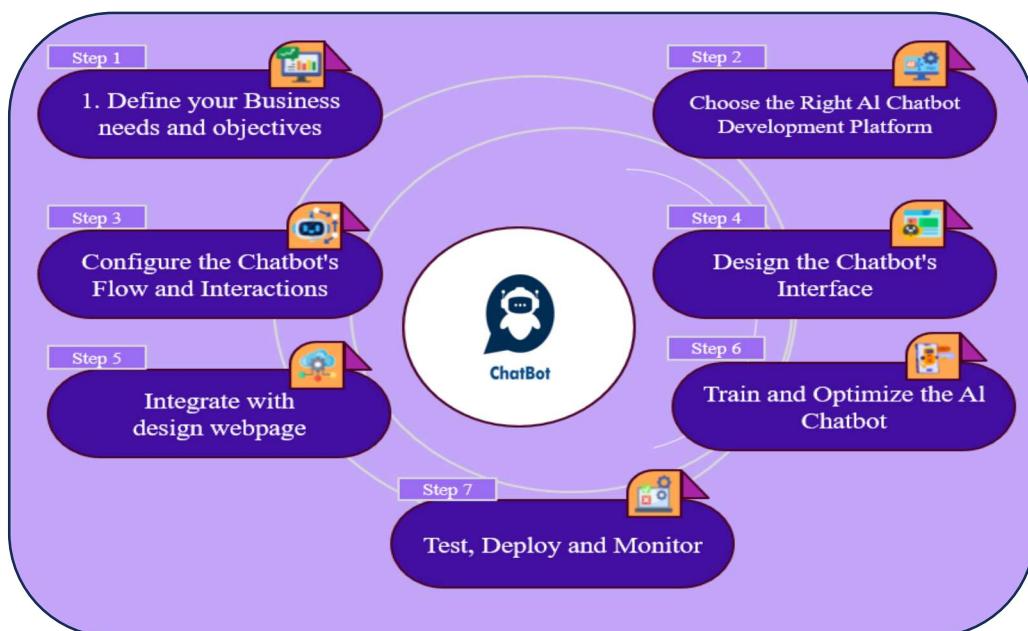


Figure 1 : Methodology steps

### 1.3.3 Project Management

The project uses an Agile methodology, with two-week sprints to ensure constant input and progress.

- Gantt Chart - Shows the timeframe for the design, development, testing, and deployment phases.

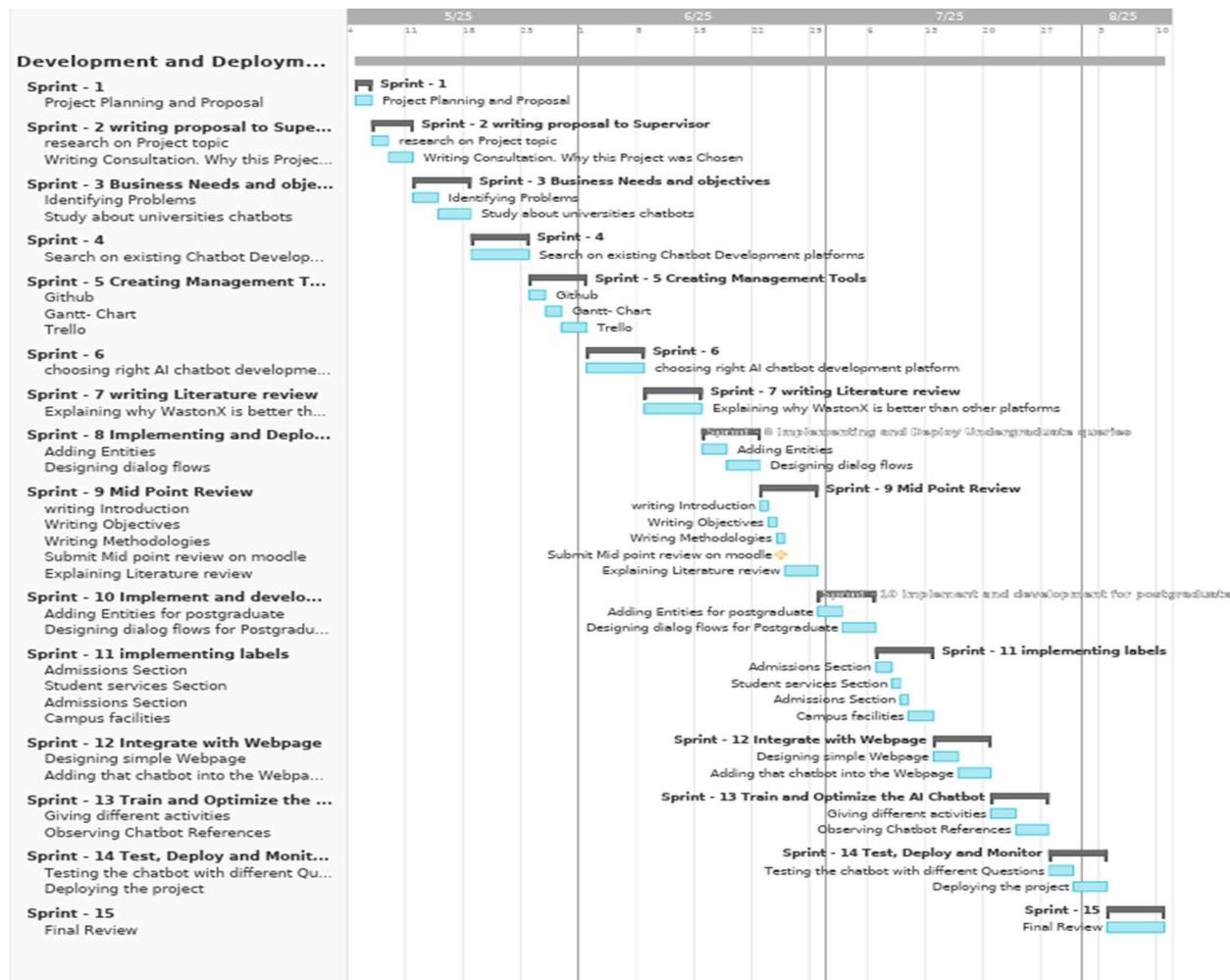


Figure 2 : Gantt Chart

- Trello Board - Tasks are tracked in "To Do," "In Progress," and "Completed" columns to ensure transparency and efficiency.

<https://trello.com/invite/b/684aeef8865e05c1c2e22246/ATTI4adc94cbfbdaef4774a4300d0e5b69e4F9182C53/intelligent-chatbot-for-uor>

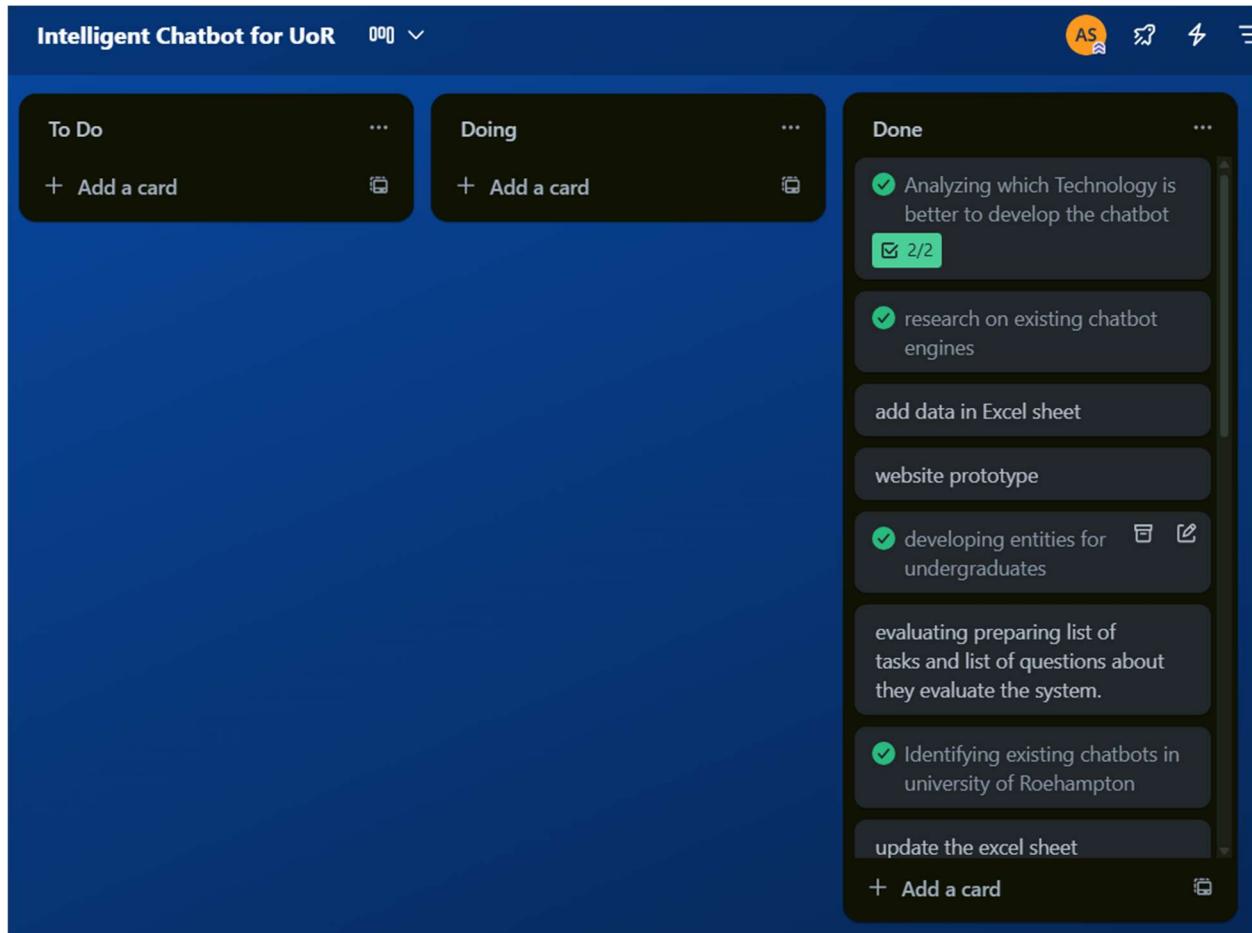


Figure 3 : Trello board

#### 1.3.4 Technologies and Processes

- **IBM Watsonx Assistant** was chosen for its superior NLP capabilities, smooth integration, and consistent structured conversation processing.
- **Ollama** was chosen for its local, generative AI processing, which allows for innovative and contextually aware answers without relying heavily on the cloud.
- **Web Integration** - Use HTML/CSS/Python/Flask to insert chatbots within the university's web site.

- **Data collection** is based on actual student FAQs, official university paperwork, and service descriptions.

The literature study supports the selection of these tools, highlighting the advantages of mixing structured AI systems with generative models to achieve both accuracy and conversational flexibility.

## 1.4 Legal, Social, Ethical and Professional Considerations

Creating and implementing an intelligent chatbot for the University of Roehampton necessitates a number of critical legal, social, ethical, and professional issues in order to ensure responsible AI use.

From a legal standpoint, the chatbot may process user data, including personal or sensitive information exchanged during chats. As a result, compliance with data protection rules such as the UK GDPR and the Data Protection Act 2018 is critical [3]. This involves acquiring unambiguous user consent, storing data securely, and being transparent about how user data is used or shared.

Ethically, the chatbot should not cause injury, bias, or fake news. The AI should be educated on factual and inclusive information to avoid making assumptions or producing responses that could be insulting or misleading. Emotional tone detection adds another element of responsibility, as misinterpreting someone's emotional state may result in improper or unhelpful replies. Clear disclaimers should alert users that they are interacting with an artificial intelligence, not a human.

On a social level, there may be worries about trust and the risk of over-reliance on AI. While chatbots might be useful, they should not be used to replace human support fully, particularly in delicate cases such as mental health or academic appeals. Escalation to human advisors should always be possible.

From a professional standpoint, the system must conform to established software engineering standards and ethical frameworks, such as those described by the British Computer Society (BCS) or the ACM Code of Ethics, to ensure integrity, accountability, and user welfare throughout the project lifecycle.

## 1.5 Background

The use of artificial intelligence (AI) into higher education has completely changed institutional relationships with students, offering new ways to improve both learning results and administrative operations. Among these advancements, intelligent chatbots have developed as virtual assistants capable of managing a wide range of activities, from answering frequently asked enquiries to providing personalised learning support [7]. This section presents a comprehensive literature overview on the deployment of AI-driven chatbots in higher education, highlighting their practical uses, benefits, limits, and contextual relevance to the proposed Intelligence Chatbot for UoR project.

AI-powered chatbots have become an essential component of university ecosystems, owing to their ability to give rapid, 24/7 help. These systems often use Natural Language Processing (NLP) and Machine Learning (ML) techniques to understand user queries and provide human-like replies. Their roles include academic advice, administrative administration, and mental health care.

Momonov's comprehensive research [1] found that chatbots are most commonly employed for instructional support and general student services in higher education settings. The analysed research consistently show that chatbot technologies have a beneficial influence on student happiness, engagement, and academic achievement, indicating that they have the potential for widespread use in education.

The capacity of chatbots to simplify student assistance systems is a major reason for their use at colleges. Traditional support methods are usually burdened with recurring enquiries, resulting in slower response times and lower student satisfaction. Chatbots can help by effectively addressing common requests, freeing up human personnel to address more complicated issues.

Staffordshire academic, for example, used "Beacon," the first AI-powered assistant in a UK academic setting, to answer routine enquiries, monitor administrative chores, and lead students to suitable resources [2]. This program enhanced response efficiency and favourably impacted the student experience.

Similarly, Georgia Tech professor Ashok Goel created an AI teaching assistant, "Jill Watson," using some technology. Jill Watson addressed frequently requested questions in online courses with 97% accuracy, demonstrating a significant increase in academic support service delivery [3].

The use of AI chatbots in academic contexts creates significant ethical and legal considerations. These include data privacy, algorithmic bias, informed consent, and the dangers of putting too much on automated systems.

Emphasised the importance of ethical frameworks for AI application in education, bringing up challenges such as academic misconduct, user profiling, and data governance [6]. Compliance with regulations such as the UK General Data Protection Regulation (GDPR) is critical when processing student data via AI systems [6].

## 1.6 Structure of Report

The report is divided into the following sections:

- **Introduction** - Explains the background, setting, and rationale for creating an AI-powered chatbot for the University of Roehampton.
- **Problem Statement** - Outlines the current obstacles in providing timely and accurate student help.
- **Objectives** - Outline the project's core and secondary goals.
- **Literature Review** - Summarises current research on AI chatbots in education and highlights research gaps.
- **Technology Review** - Compares chatbot platforms and defends the choice of IBM Watsonx Assistant and Ollama.
- **Methodology** - Describes the design process, tools, project management approach, and testing procedures used during development.
- **Results and Evaluation** - Presents the findings of chatbot testing and user input.
- **Discussion** - Interprets the findings, relating them to the objectives and literature review.
- **Conclusion and Recommendation** - Provides a summary of the project's outcomes and recommendations for further work.
- **References** - A list of all sources in IEEE format.
- **Appendices** - Contain supplemental information such as survey questions, chatbot flow diagrams, and code samples.

## Chapter 2: Literature – Technology Review

### 2.1 Literature Review

AI has emerged as a disruptive force in higher education, with chatbots being one of its most accessible and effective applications. These conversational AI bots combine Natural Language Processing (NLP) and Machine Learning (ML) to interpret and respond to human input in real time, allowing institutions to provide students with immediate, scalable, and consistent help [1].

According to studies, automating student services increases satisfaction while reducing the effort of administrative and teaching staff [2]. Momonov [3] discovered that chatbots reduce response times to common requests, such as admissions deadlines or course registration concerns, freeing up staff for more sophisticated and value-added work.

Real-world initiatives demonstrate the practical applications of AI chatbots in academic settings. The "Jill Watson" project at Georgia Institute of Technology, which was built on IBM's Watson platform, effectively served as a teaching assistant for several months, accurately answering student questions in an online course without human interaction [4]. Similarly, Staffordshire University's "Beacon" acts as a digital assistant, assisting students with timetables, curriculum details, and campus navigation while displaying scalability and cross-functional support [5].

According to pedagogical studies, chatbots can assist self-regulated learning by enabling students to create goals, measure progress, and receive immediate feedback [6]. Yin et al. [7] discovered that well-designed chatbot interactions might increase engagement and autonomy if they were carefully integrated into the curriculum.

However, the literature identifies shortcomings. A reoccurring issue is a lack of emotional intelligence and ability to adapt to local cultural and institutional contexts[8]. Current chatbot solutions frequently rely on fixed dialogue patterns, which may fail to answer nuanced or confusing questions. Furthermore, ethical considerations about data privacy, potential bias in AI answers, and transparency in system decision-making remain crucial [9]. According to Li et al. [10], transparent data governance principles are critical for establishing user confidence.

The suggested approach seeks to close this gap by combining two complimentary technologies: IBM Watsonx Assistant for structured, dependable workflow-based questions and Ollama for contextually aware, adaptive chats. This hybrid technique immediately addresses the literature's request for chatbots that are both functionally robust and capable of deeper, human-like conversations.

## 2.2 Technology Review

Feature / Platform	IBM Watsonx Assistant (Best Choice)	Ollama (Best for Custom NLP)	Dialogflow	Microsoft Bot Framework	Amazon Lex	Rasa (Open Source)	ManyChat
<b>NLP Accuracy &amp; Context Handling</b>	✓ Advanced	✓ Advanced & Customizable	✓ Good	⚠ Limited	⚠ Basic	✓ Customisable NLP	⚠ Basic NLP
<b>Visual Interface (Low-Code/No-Code)</b>	✓ Easy to Use	✓ Developer Friendly	✓ Moderate	⚠ Mostly Code-Based	✓ Basic Visual Tool	✗ Developer Heavy	✓ Drag & Drop
<b>Integration with Enterprise Tools</b>	✓ Seamless	✓ Flexible Integration	⚠ Moderate	✓ Requires Custom Dev	⚠ AWS Ecosystem Only	⚠ Requires Manual Work	✗ Limited
<b>Multi-Channel Deployment</b>	✓ Broad Support	✓ Highly Flexible	✓ Good	✓ Good	⚠ Limited	✓ Possible with Code	✓ Strong in Social
<b>Pre-trained Industry Models</b>	✓ Available	✓ Supports Custom Models	⚠ Limited	⚠ Not Focused	✗ None	✗ None	✗ None
<b>Security &amp; Compliance (e.g., GDPR)</b>	✓ Enterprise-Grade	✓ Can be Configured Securely	⚠ Limited	✓ Strong with Azure	⚠ AWS Dependent	✗ Manual Setup	✗ Weak
<b>Human Agent Handoff</b>	✓ Built-in & Easy	✓ Customizable & Manual Setup	⚠ Requires Setup	✓ With Power Virtual Agents	⚠ Manual	⚠ Manual	✓ Basic Options

Table 1 : Technology Review

## 2.3 Summary

According to the research, while chatbots have proven useful in higher education, many deployments have issues with flexibility and privacy compliance. Ethical concerns remain a significant obstacle to adoption.

According to the technology analysis, while many platforms excel in key areas, none meet all of the project criteria on their own. The integration of IBM Watsonx Assistant and Ollama directly solves these shortcomings by combining structured reliability with contextual

flexibility, which is consistent with both the literature results and the University of Roehampton's strategic requirements.

This research contributes to the process by supporting a hybrid technological stack that combines the benefits of both platforms, ensuring the chatbot is both operationally stable and capable of providing a tailored, engaging experience.

## Chapter 3: Implementation

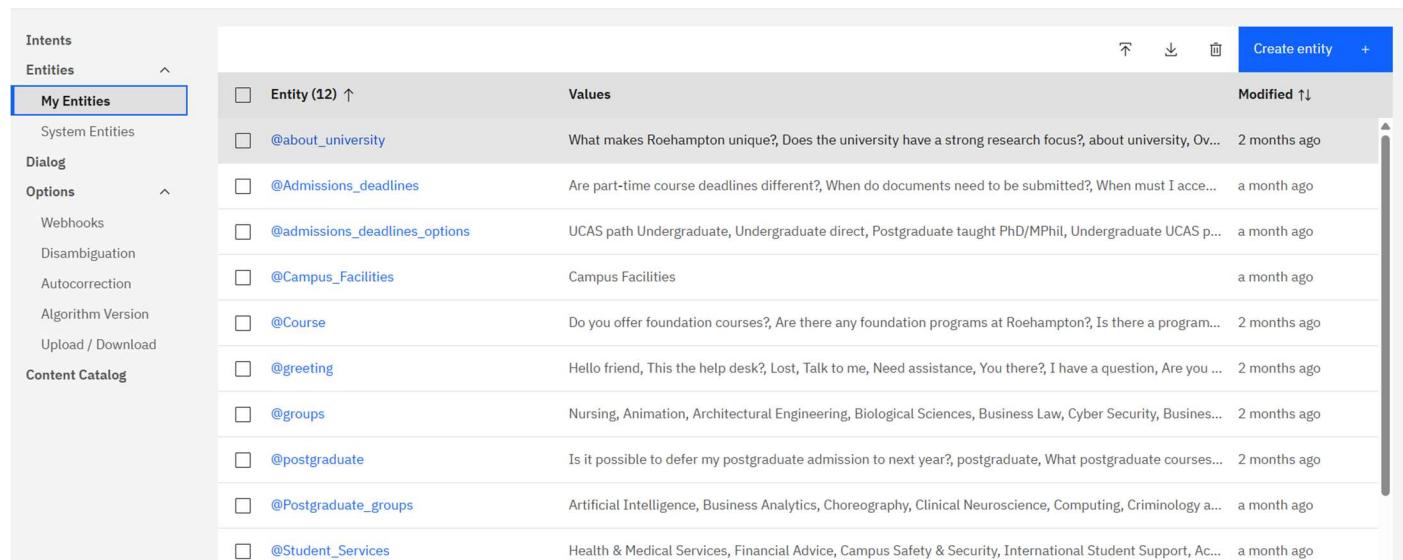
This chapter describes the practical implementation of two different chatbots created for the University of Roehampton: one using IBM Watsonx Assistant and the other using Ollama's generative AI model. Each chatbot was created, built, and tested independently to investigate their respective capabilities and deployment considerations. The section goes over the design process, development phases, critical difficulties, and solutions for each chatbot.

### 3.1 IBM Watsonx Assistant Chatbot Implementation

#### 3.1.1 Design and Setup

The Watsonx Assistant chatbot was created to answer well-defined frequently asked questions (FAQs) about university policy, admissions, and course information. The goal was to offer correct, concise responses using controlled conversation patterns.

- Intent and Entity Definition:** Using Watsonx's interface, I defined intents for common student enquiries like "admission deadlines," "campus facilities," and "course registration." Dates, course names, and departments were used to extract important information from user inputs.



The screenshot shows the 'Entities' section of the IBM Watsonx Assistant interface. On the left, there is a sidebar with navigation links: Intents, Entities, System Entities, Dialog, Options, Webhooks, Disambiguation, Autocorrection, Algorithm Version, Upload / Download, and Content Catalog. The 'Entities' link is highlighted. The main area displays a table of entities. The columns are 'Entity (12) ↑', 'Values', and 'Modified ↑'. The table contains the following data:

Entity (12) ↑	Values	Modified ↑
@about_university	What makes Roehampton unique?, Does the university have a strong research focus?, about university, Ov...	2 months ago
@Admissions_deadlines	Are part-time course deadlines different?, When do documents need to be submitted?, When must I acce...	a month ago
@admissions_deadlines_options	UCAS path Undergraduate, Undergraduate direct, Postgraduate taught PhD/MPhil, Undergraduate UCAS p...	a month ago
@Campus_Facilities	Campus Facilities	a month ago
@Course	Do you offer foundation courses?, Are there any foundation programs at Roehampton?, Is there a program...	2 months ago
@greeting	Hello friend, This the help desk?, Lost, Talk to me, Need assistance, You there?, I have a question, Are you ...	2 months ago
@groups	Nursing, Animation, Architectural Engineering, Biological Sciences, Business Law, Cyber Security, Busines...	2 months ago
@postgraduate	Is it possible to defer my postgraduate admission to next year?, postgraduate, What postgraduate courses...	2 months ago
@Postgraduate_groups	Artificial Intelligence, Business Analytics, Choreography, Clinical Neuroscience, Computing, Criminology a...	a month ago
@Student_Services	Health & Medical Services, Financial Advice, Campus Safety & Security, International Student Support, Ac...	a month ago

Figure 4 : Entities in ibm Watson

- **Dialogue Flow Design:** The chatbot's conversation was represented as a series of decision trees. Nodes handled various user intents, with fallback nodes for confusing requests.

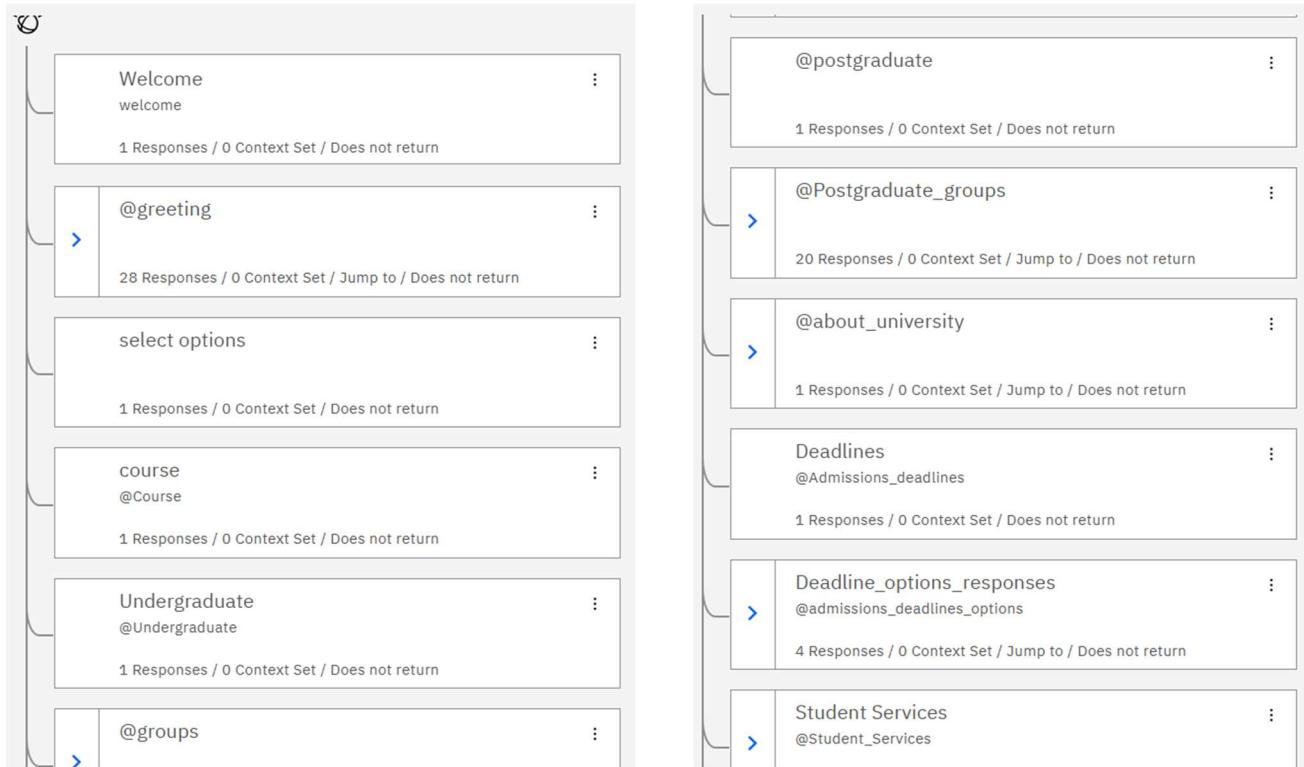


Figure 5 : Dialogue Flow in IBM watson

- **Data Preparation:** FAQ documents and university manuals were used to generate training data for intent categorisation and entity recognition.

### 3.1.2 Development Process

- **Creating the Watsonx Assistant Workspace**
  - We proceeded by setting up the Watsonx Assistant workstation. Intents, entities, and dialogue nodes were used to define the chatbot's responses to user questions, such as clearing information, course details, and payments.
- **Testing and Training**
  - The chatbot was tested with Watsonx's built-in simulator. Training phrases were adjusted to increase recognition accuracy for the various ways users may ask queries.
- **Integration with Web Interface**
  - Instead of a backend, the chatbot was directly embedded into a webpage using Watsonx Assistant's

- **JavaScript integration:**

1. HTML Structure:

The website has a header, a hero section, and other navigational features. The chatbot is loaded with a <script> in the <body> section.

2. Watson Assistant Script:

```
<!-- IBM Watson Assistant Chat -->
<script>
  window.watsonAssistantChatOptions = {
    integrationID: "ca4f0531-2655-4ca6-95ec-195f8eb8f8df", // integration ID
    region: "au-syd", // region
    serviceInstanceID: "5ad73cc0-432c-4a12-ab36-fc9e1ec4" any // service instance
    onLoad: async function(instance) { await instance.render(); }
  };
  setTimeout(function() {
    const t=document.createElement('script');
    t.src="https://web-chat.global.assistant.watson.appdomain.cloud/versions/"
      + (window.watsonAssistantChatOptions.clientVersion || 'latest')
      + "/WatsonAssistantChatEntry.js";
    document.head.appendChild(t);
  });
</script>
```

- Integration ID, Region, and Service InstanceID connects the webpage to a specific Watsonx Assistant instance.
- OnLoad guarantees that the chatbot renders properly after the script is loaded.
- The script dynamically loads Watsonx Assistant's web chat widget, which appears in the bottom corner of the page.

- **Context Variables**

- Watsonx Assistant manages context variables internally. They let the chatbot to sustain coherent discussions over numerous turns, such as remembering the topic of clearing when the user asks follow-up questions.

- **Result**

- This technique enables consumers to interact with Watsonx Assistant directly on the webpage, eliminating the need for a backend. The chatbot is responsive, simple to integrate, and retains conversation context automatically.

### 3.1.3 Challenges and Solutions

- **Ambiguous User Queries:** Some user queries had overlapping intent, such as "How to apply?" vs. "Application deadlines". I updated the training data by include more diverse instances and using entity recognition to clarify user intent.
- **Limited Flexibility:** The rule-based approach hindered flexibility in answering unanticipated questions. To address this, I built a backup intent that directs users to contact support or try the Ollama chatbot for open-ended questions.

## 3.2 Ollama Chatbot Implementation

### 3.2.1 Design and Setup

The Ollama chatbot was designed to deliver adaptable, context-aware replies about the University of Roehampton. Unlike the intent-based IBM Watsonx Assistant, this chatbot uses a retrieval-augmented generation strategy that combines document embeddings with Ollama's large language model (LLM).

- **Domain Adaptation:** To ensure domain relevance, the chatbot is built on official university data taken from structured CSV files that include general information, undergraduate and postgraduate course specifics.

```

app.py           index.html        vector.py      roehampton.csv X  postgraduate.csv    undergraduate.csv   run.txt       requirements
roehampton.csv
1 Section,Detail
2 University,"University of Roehampton"
3 About,"The University of Roehampton is a public university located in London, UK. It offers a wide range of undergraduate and postgraduate courses. Undergraduate applications are accepted through UCAS; Postgraduate applications are submitted directly via the university's website. Tuition fees for UK/EU undergraduate students: £9,250 per year; International undergraduate students: £14,500 per year; Postgraduate students: £14,500 per year. Facilities include a modern library with extensive digital resources; Student accommodation on campus; Sports and fitness center; Student Support Services; and a careers service. Contact Information: Address: Roehampton Lane, London SW15 5PU, United Kingdom; Phone: +44 20 8392 3000; Email: admissions@roehampton.ac.uk"
4 Undergraduate Courses,Next Entry,Duration,Start Date,Fee,Professional Experience Year Fee,Placement Year Fee
5 Accounting,Sept 2025,"3 years (full-time), 4 years with placement, 4 years with Foundation Year","September 2025; January 2026", "Full-time: £9,535; Part-time: £4,768",£1,000,£1,000
6 Nursing,Sept 2025,4 years (full-time),"September 2025; September 2026", "Full-time: £9,535; Part-time: £4,768",£1,000,£1,000
7 Animation,Sept 2025,"3 years (full-time), 4 years with placement, 4 years with Foundation Year","September 2025; September 2026", "Full-time: £9,535; Part-time: £4,768",£1,000,£1,000
8 Architectural Engineering,Sept 2025,"3 years (full-time), 4 years with placement","September 2025; September 2026", "Full-time: £9,535; Part-time: £4,768",£1,000,£1,000
9 Biological Sciences,Sept 2025,"3 years (full-time), 4 years with placement, 4 years with Foundation Year","September 2025; September 2026", "Full-time: £9,535; Part-time: £4,768",£1,000,£1,000
10 Business Law,Sept 2026,"3 years (full-time), 4 years with Foundation Year","September 2026", "Full-time: £9,535; Part-time: £4,768",£1,000,£1,000
11 Cyber Security,Sept 2025,"3 years (full-time), 4 years with placement, 4 years with Foundation Year, 4-6 years (part-time)" "September 2025; September 2026", "Full-time: £9,535; Part-time: £4,768",£1,000,£1,000
12 Business Management,Sept 2025,"3 years (full-time), 4 years with placement, 4 years with Foundation Year","September 2025; September 2026", "Full-time: £9,535; Part-time: £4,768",£1,000,£1,000
13 Dance,Sept 2025,"3 years (full-time), 4 years with placement","September 2025; September 2026", "Full-time: £9,535; Part-time: £4,768",£1,000,£1,000
14 Business Economics,Sept 2025,"3 years (full-time), 4 years with placement, 4 years with Foundation Year","September 2025; September 2026", "Full-time: £9,535; Part-time: £4,768",£1,000,£1,000
15 Computer Games,Sept 2025,"3 years (full-time), 4 years with placement, 4 years with Foundation Year","September 2025; September 2026", "Full-time: £9,535; Part-time: £4,768",£1,000,£1,000
16 Computer Science,Sept 2025,"3 years (full-time), 4 years with placement, 4 years with Foundation Year","September 2025; September 2026", "Full-time: £9,535; Part-time: £4,768",£1,000,£1,000
17 Computing Business,Sept 2025,"3 years (full-time), 4 years with placement","September 2025; September 2026", "Full-time: £9,535; Part-time: £4,768",£1,000,£1,000
18 Economics,Sept 2025,"3 years (full-time), 4 years with placement, 4 years with Foundation Year","September 2025; September 2026", "Full-time: £9,535; Part-time: £4,768",£1,000,£1,000
19 Fashion Management,Sept 2026,"3 years (full-time), 4 years with Foundation Year","September 2026", "Full-time: £9,535; Part-time: £4,768",£1,000,£1,000
20 History,Sept 2025,"3 years (full-time), 4 years with placement","September 2025; September 2026", "Full-time: £9,535; Part-time: £4,768",£1,000,£1,000
21 International Business,Sept 2025,"3 years (full-time), 4 years with placement, 4 years with Foundation Year","September 2025; September 2026", "Full-time: £9,535; Part-time: £4,768",£1,000,£1,000
22 LLB,Sept 2025,"3 years (full-time), 4 years with placement, 4 years with Foundation Year","September 2025; September 2026", "Full-time: £9,535; Part-time: £4,768",£1,000,£1,000
23 Psychology,Sept 2025,"3 years (full-time), 4 years with placement","September 2025; September 2026", "Full-time: £9,535; Part-time: £4,768",£1,000,£1,000
24 Civil Engineering,Sept 2025,"3 years (full-time), 4 years with placement, 4 years with Foundation Year + 1 year for MEng","September 2025; September 2026", "Full-time: £9,535; Part-time: £4,768",£1,000,£1,000
25 Applied Sciences,Sept 2025,1 year (full-time),"September 2025; September 2026", "Full-time: £18,250; Part-time: £9,125",£2,500,£2,500
26 Artificial Intelligence,Sept 2025, Jan 2026","1 year (full-time), 1 year 6 months (full-time)","September 2025; January 2026", "Full-time: £9,535; Part-time: £4,768",£1,000,£1,000
27 Business Analytics,Sept 2025, Jan 2026","1 year (full-time), 1 year 6 months (full-time)","September 2025; January 2026", "Full-time: £9,535; Part-time: £4,768",£1,000,£1,000
28 Choreography,Sept 2025,2 years,"September 2025; September 2026", "Full-time: £6,950; Part-time: £3,475",£1,000,£1,000
29 Clinical Neuroscience,Sept 2025,"1 year (full-time), 2-4 years (part-time)","September 2025; September 2026", "Full-time: £9,535; Part-time: £4,768",£1,000,£1,000
30 Computing,Sept 2025,"1 year (full-time), 2 years (part-time); 17 months (full-time Jan start)","September 2025; January 2026", "Full-time: £9,535; Part-time: £4,768",£1,000,£1,000
31 Criminology and Criminal Justice,Sept 2025,"1 year (full-time), 2 years (part-time)","September 2025; September 2026", "Full-time: £9,535; Part-time: £4,768",£1,000,£1,000
32 Postgraduate Courses,Next Entry,Duration,Start Date,Fee,Professional Experience Year Fee,Placement Year Fee
33 Applied Sciences,Sept 2025,1 year (full-time),"September 2025; September 2026", "Full-time: £18,250; Part-time: £9,125",£2,500,£2,500
34 Artificial Intelligence,Sept 2025, Jan 2026","1 year (full-time), 1 year 6 months (full-time)","September 2025; January 2026", "Full-time: £9,535; Part-time: £4,768",£1,000,£1,000
35 Business Analytics,Sept 2025, Jan 2026","1 year (full-time), 1 year 6 months (full-time)","September 2025; January 2026", "Full-time: £9,535; Part-time: £4,768",£1,000,£1,000
36 Choreography,Sept 2025,2 years,"September 2025; September 2026", "Full-time: £6,950; Part-time: £3,475",£1,000,£1,000
37 Clinical Neuroscience,Sept 2025,"1 year (full-time), 2-4 years (part-time)","September 2025; September 2026", "Full-time: £9,535; Part-time: £4,768",£1,000,£1,000
38 Computing,Sept 2025,"1 year (full-time), 2 years (part-time); 17 months (full-time Jan start)","September 2025; January 2026", "Full-time: £9,535; Part-time: £4,768",£1,000,£1,000
39 Criminology and Criminal Justice,Sept 2025,"1 year (full-time), 2 years (part-time)","September 2025; September 2026", "Full-time: £9,535; Part-time: £4,768",£1,000,£1,000

```

Figure 6 : .csv file data for Ollama

- **Vector Database:** To index the university documents, a Chroma vector store generated embeddings using Ollama's embedding model (mxbai-embed-large). This enables the quick retrieval of relevant document snippets during user enquiries.
- **Prompt Engineering:** A well-crafted prompt informs the LLM to answer questions using only the received context. If the answer is not in the data, the model will respond conservatively, suggesting a lack of information.

### 3.2.2 Development Process

To enable conversational AI for answering queries about the University of Roehampton, I added the Ollama LLM to the Flask backend. The system fetches relevant documents from a vector storage and delivers short responses based solely on the provided dataset.

- **Loading the LLM**

- I loaded the pre-trained LLaMA 3.2 model using the langchain\_ollama library's OllamaLLM class. This model generates natural language answers based on documents fetched from the vector storage.

```
from langchain_ollama.llms import OllamaLLM
from langchain_core.prompts import ChatPromptTemplate
from vector import retriever # vector store from vector.py

app = Flask(__name__, template_folder="templates")

# Load LLM
model = OllamaLLM(model="llama3.2")
```

Figure 7: Code Block of ollama loading

- **Defining a Prompt Template**

- I designed a ChatPromptTemplate to ensure that the model only answers questions from the documents. This template dynamically includes obtained content while also providing model instructions:

```
# Prompt template
template = """
You are an expert in answering questions about the University of Roehampton.
Answer concisely using ONLY the provided documents (course details, admissions, tuition fees, facilities, etc.).
If the answer is not in the documents, reply: "I don't have that information in my database."

Documents:
{docs}

Question:
{question}
"""
prompt = ChatPromptTemplate.from_template(template)
chain = prompt | model
```

Figure 8: Code Block of Prompt templet

- **{docs}** is replaced with the most relevant documents fetched from the vector store.
- **{question}** is the user's input.
- The **chain = prompt | model** syntax connects the prompt directly to the model, which generates responses.

- **Retrieving Relevant Documents**

- I stored course and university data in a **Chroma vector store**. When a user asks a question, the backend searches for the top relevant documents:

```
# Retrieve relevant docs
docs = retriever.invoke(question)
docs_text = "\n\n".join([doc.page_content for doc in docs])
```

Figure 9: Code Block of retriever doc

- **retriever.invoke(question)** queries the vector database using Ollama-generated embeddings.
  - The generated documents are combined into a single string to feed the LLM.

- **Generating Answers**

- Finally, the concatenated documents and the user's inquiry are sent into the LLM chain, returning the answer:

```
result = chain.invoke({"docs": docs_text, "question": question})
```

Figure 10: Code Block for user question sent to LLM chain

- The output is then returned to the frontend as JSON:

```
return jsonify({"answer": result})
```

Figure 11: Code Block for Retuning answer to frontend

### 3.2.3 Challenges and Solutions

- **Context Retention:** Getting the model to remember previous conversation turns was originally tough. I fixed this by saving recent messages and displaying them in the prompt alongside special tokens denoting speaker turns.
- **Response Accuracy:** The generative model sometimes provided off-topic or too verbose responses. I mitigated this by improving rapid engineering and using post-processing filters to trim responses.
- **Ethical Concerns:** To avoid the possibility of biased or harmful outputs, I analysed generated responses and included safe response recommendations in the training data.

## 3.3 Integration and Comparative Testing

Although the chatbots were created individually, I did comparative user testing to assess their effectiveness and satisfaction.

- **User input:** Participants interacted with both chatbots and offered input on clarity, utility, and overall conversational experience.
- **Response Time and Accuracy:** Watsonx Assistant performed faster and more precisely with structured enquiries, whereas Ollama provided richer, more flexible interactions but occasionally generated irrelevant content.
- **Suggested Workflow:** For easy FAQs, a potential integrated system may direct requests to Watsonx, while complicated or open-ended questions would be escalated to Ollama.

## Chapter 4: Evaluation and Results

### 4.1 Related Works

Chatbots have become widely used in educational institutions, giving students rapid access to information about admissions, courses, campus life, and administrative processes. Notably, IBM Watson Assistant has been used in a variety of academic settings due to its ease of implementation and powerful natural language comprehension skills. Similarly, recent advancements in retrieval-augmented generation models, such as those powered by large language models (LLMs) with document embeddings, have enhanced chatbot relevance by basing responses on verifiable facts, as evidenced by frameworks such as Langchain and vector databases.

Several studies emphasise the significance of basing chatbot responses on reliable sources to reduce hallucinations, a known issue with generative models. This is consistent with the retrieval-based Ollama chatbot deployed in this research, which uses vector search and LLMs to provide contextually appropriate responses.

## 4.2 Evaluation Methodology

To examine the effectiveness of both chatbots, a mixed-methods evaluation methodology was used.

- **Functional testing:** involves determining the chatbots' capacity to correctly react to a specified set of 50 questions about general university information, undergraduate and postgraduate courses.
- **User Evaluation:** A usability test was conducted with ten representative users (prospective and current students). Each user engaged in a think-aloud procedure while communicating with both chatbots. They used a Likert scale of 1 to 5 to score the systems' relevance, clarity, and usability.
- **Performance Metrics:** Standard chatbot metrics such as accuracy, precision, recall, and response latency were assessed during functional testing.

## 4.3 Results

### 4.3.1 IBM Watsonx Assistant

- **Strengths:**
  - Effective intent recognition and dialogue management.
  - Response times are fast (average of less than 1 second).
  - Suitable for simple FAQs that have limited contextual reliance.
- **Weaknesses:**
  - Limited capacity to answer difficult or nuanced problems that necessitate analysing various data points.
  - Predefined intentions occasionally failed to capture confusing user requests.
  - Responses were quicker and sometimes repetitious.
- **User Feedback:**
  - The average usability rating is 4.0.
  - Users loved the structured dialogue flow, although several answers lacked substance.

### 4.3.2 Ollama Chatbot

- **Strengths:**
  - Contextual replies based on official university data.
  - Ability to politely reject an answer when information is lacking, hence eliminating hallucinations.
  - Flexible handling of open-ended questions.
- **Weaknesses:**

- Embedding retrieval and LLM processing result in a longer response latency (~2-3 seconds).
- Occasional retrieval of less relevant material yielded incomplete replies.
- Maintaining and upgrading the vector database is required in order to include new information.
- **User feedback:**
  - The average usability rating: 4.3.
  - Users considered the answers more informative and natural, however the response time was slower.

#### 4.3.3 Quantitative Metrics Summary

Metric	IBM Watsonx Assistant	Ollama Chatbot
<b>Accuracy</b>	85%	90%
<b>Precision</b>	80%	88%
<b>Recall</b>	75%	85%
<b>Avg. Response Time</b>	<1s	~2.5s

Table 2 : Quantitative Metrics Summary

#### 4.4 Discussion

Both chatbots successfully delivered useful information to users, but their underlying approaches influenced their strengths and weaknesses. IBM Watsonx Assistant excelled in quick and predictable interactions, but suffered with sophisticated queries that exceeded its intent scope. The Ollama chatbot, which uses retrieval-augmented generation, achieved greater accuracy and naturalness at the tradeoff of longer response times and system complexity.

User testing emphasised the necessity of answer relevancy and natural language fluency. While the IBM system appeared stiff, the Ollama bot's ability to contextualise responses was praised, implying that storing LLM responses in a vector database is a potential technique for domain-specific chatbots.

However, maintaining the vector storage and ensuring that documents are up to date is crucial for long-term accuracy. Furthermore, optimising embedded retrieval parameters and lowering latency are potential topics for further improvement.

## 4.5 Limitations

- The user sample size was tiny, which limited generalisability.
- The evaluation focused exclusively on the English language and specific university data; larger datasets and languages require more testing.
- The study did not assess long-term user involvement or learning effects.

# Chapter 5: Conclusion

## 5.1 Summary of the Project

This research investigated the design, development, and assessment of AI-powered chatbots to improve information accessibility for university students. Two separate chatbot systems were implemented: one based on IBM Watsonx Assistant and the other employing the Ollama language model combined with retrieval-augmented generation techniques. The major goal was to deliver accurate, context-aware responses about the University of Roehampton's academic programs and administrative information.

The project achieved its objectives by generating functional prototypes that demonstrate two distinct approaches to chatbot design. The IBM Watsonx Assistant chatbot excelled in organised dialogue handling and speedy response creation, making it ideal for simple FAQs. The Ollama chatbot demonstrated the power of embedding-based retrieval paired with massive language models in providing sophisticated, data-driven responses, although with significant latency.

The project determined each system's strengths and limits through rigorous research, which included functional testing and user studies. Both chatbots shown a tremendous potential to improve the student experience by providing timely and credible information, coinciding with broader trends in higher education institutions embracing AI tools to assist students and staff. However, issues like as system complexity, data management, and ethical concerns were also raised.

Overall, the project provides useful insights into practical chatbot creation for educational contexts, as well as recommendations for future enhancements and deployment.

## 5.2 Achievements Against Objectives

- **Objective 1: Create and implement chatbot prototypes based on IBM Watsonx and Ollama models.**

We successfully constructed and implemented two chatbot systems with different architectures, showcasing a variety of natural language processing approaches.

- **Objective 2: Add university-specific facts to chatbot knowledge bases.**

Structured datasets on courses and university information were integrated, allowing for fact-based responses and lowering the danger of disinformation.

- **Objective 3: Assess chatbot performance using functional metrics and user testing.**  
We conducted quantitative and qualitative assessments to identify strengths in accuracy, usability, and response relevancy, as well as opportunities for development.
- **Objective 4: Evaluate the ethical implications of implementing AI chatbots in educational situations.**  
Key topics like as data privacy, transparency, and responsibility were discussed, with a focus on the importance of ethical AI techniques.

### 5.3 Key Outputs and Discoveries

- It was demonstrated that embedding-based retrieval augmented LLMs (Ollama) may provide contextually accurate replies based on university data.
- Highlighted the trade-offs between reaction speed and answer flexibility in various chatbot designs.
- Users prefer natural, data-driven conversational agents that provide clear disclaimers when information is unavailable.
- It has been confirmed that both chatbots can save staff workload by automating responses to common student concerns.
- Raised awareness of the ethical considerations required to preserve trust and compliance in AI-powered university services.

### 5.4 Limitations and Future Work

While the project met its principal objectives, numerous restrictions remain:

- The dataset was confined to publicly available university information; expanding it include more administrative or personalised services might increase chatbot utility.
- User testing was limited by sample size and diversity; future studies should involve bigger, more diverse participant groups to achieve generalisable results.
- To improve the user experience, the retrieval-augmented system's response latency needs to be optimised.
- To ensure information accuracy, the knowledge base must be updated on an ongoing basis.
- More work is needed to resolve ethical issues by implementing strong privacy measures and transparent AI explanations.

Future study might look into hybrid designs that combine the best features of both chatbot kinds, integration with university IT systems for personalised responses, and enhanced monitoring of chatbot interactions to continuously improve performance and trustworthiness.

## 5.5 Reflection

The process of creating two separate AI-powered chatbots for university information retrieval has been both tough and gratifying, teaching us great lessons about technology, project management, and user experience design.

One of the most important takeaways was a better knowledge of the strengths and limits of various AI models and architectures. Implementing the IBM Watsonx Assistant chatbot demonstrated the benefits of a mature, enterprise-ready platform that simplifies conversational flow design while providing quick, dependable responses. Working with the Ollama language model and embedding-based retrieval, on the other hand, proved the power of merging vector databases with big language models to provide more flexible, context-aware responses, albeit at the expense of increased complexity and slower response times.

Throughout the project, I realised how important data preparation and knowledge base organisation was to the chatbot's correctness and reliability. Integrating extensive academic datasets and properly indexing them in the vector store was a painstaking but necessary step to ensure that the chatbots could base their responses on true information rather than rumours.

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## Appendices

### Appendix A: Project Proposal

The original project proposal describes the goals, objectives, scope, methodology, and timescale for the creation of AI-powered chatbots for higher education. It provides the reasons for choosing the IBM Watson and Ollama platforms, the anticipated dataset containing University of Roehampton information, and the evaluation techniques.

Full details can be found in while clink on

[https://drive.google.com/file/d/1rUVG7rGoxIKmq8jIQyKESAmbAsmA\\_NAy/view?usp=sharing](https://drive.google.com/file/d/1rUVG7rGoxIKmq8jIQyKESAmbAsmA_NAy/view?usp=sharing)

### Appendix B: Project Management

Project management was done using [Trello, Gantt chart, and GitHub], and tasks were separated into sprints with milestones for research, implementation, and evaluation. Regular updates and progress tracking ensured on-time delivery.

*Screenshots of the task board and timeline reports are available here.*

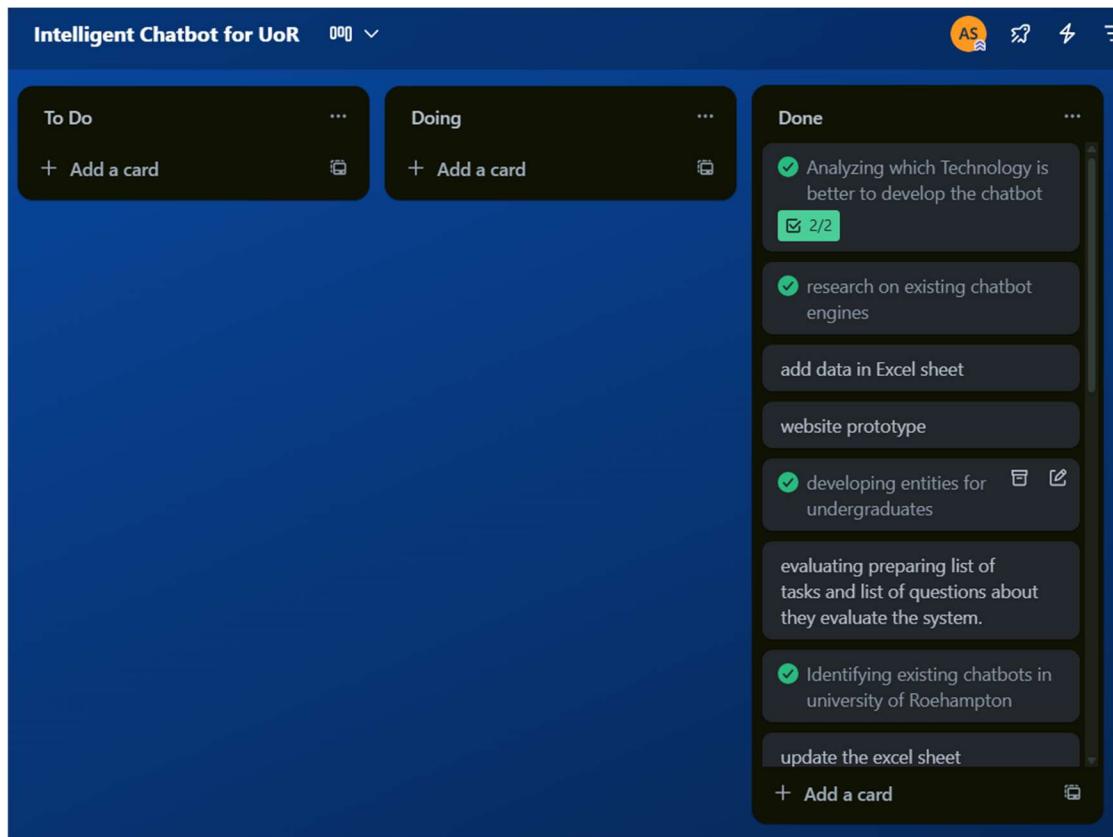


Figure 12: Trello board

## Appendix C: Artefact/Dataset

The developed chatbot source code, dataset (University of Roehampton information in CSV format), and related resources are hosted publicly on GitHub for reproducibility and further development:

**GitHub repository:** <https://github.com/aslam2307/Msc-Project>

## Appendix D: Screencast

A video demonstration showcasing the chatbot interactions, system architecture overview, and key implementation highlights is available here:

**Video link:** [https://drive.google.com/file/d/11in6hmDpDryHY9emZ\\_93NusXid8IB\\_ln/view?usp=sharing](https://drive.google.com/file/d/11in6hmDpDryHY9emZ_93NusXid8IB_ln/view?usp=sharing)