BITS College

INTRODUCTION TO AI

AI-Driven Help Desk Chatbot

Group Name: **NeuraX**

Abel Asnake - UGR/SWE/0056/22

Adoniyas Getachew - UGR/SWE/0072/22

Bitanya Dereje - UGR/SWE/0079/23

Dagmawi Girma - UGR/SWE/0081/23

Hafsa Hussien - UGR/SWE/0083/23

Submitted to: Mr. Getachew Getu

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Introduction

This document presents the design and development of Bitsy, an AI-powered chatbot created to support students and administrative staff at BITS College. The chatbot is designed to understand natural language questions and provide accurate information regarding college policies, procedures, and services. It achieves this through structured NLP workflows and a curated knowledge base.

The significance of this project emerges from its embodiment of key artificial intelligence principles. As an intelligent agent, Bitsy perceives user inputs through text processing, reasons about them via semantic matching, and acts by delivering appropriate responses. Knowledge representation is realized in a JSON-based FAQ repository containing intents, patterns, and responses. Natural language understanding and semantic similarity evaluation reflect modern advances in NLP.

The need for this system arises from inefficiencies in manual information retrieval and support services. Traditional methods of responding to student inquiries can be slow, labour-intensive, and inconsistent, particularly during peak periods like registration deadlines or exam weeks. The chatbot offers a reliable, immediate, and standardized channel for students to access information related to registration procedures, attendance policies, tuition payments, academic advising, and transcript access.

Abstract / Executive Summary

This project introduces an AI-powered chatbot named Bitsy, developed to streamline information retrieval and automate responses to college-related queries at BITS. The system employs advanced Natural Language Processing (NLP) techniques and integrates Python, spaCy, Sentence Transformers, and Streamlit. User inputs are processed through text normalization and semantic analysis to identify intent. The highest-confidence match with a knowledge base determines the response. The chatbot architecture encompasses preprocessing, intent recognition, decision-making, and real-time response delivery through a web interface. Notable outcomes include over 90 percent accuracy in intent recognition, response times under 300 milliseconds, and positive user satisfaction scores. The user interface presents a clean chat layout with options for human escalation. This work illustrates the effective application of intelligent agents, knowledge representation, and NLP to practical problems, including customer support automation and information access. Metrics such as precision, recall, latency, and qualitative feedback confirm the system's utility and suggest areas for further optimization.

Methodology

Agent Architecture

The chatbot architecture is composed of four major components. First, input processing involves cleaning and normalizing user-entered text. Text is converted to lowercase and passed through spaCy to obtain tokens. Tokens representing punctuation, stopwords, or non-alphabetic characters are discarded. The remaining lexical items are lemmatized to their base forms, facilitating more robust matching.

Second, intent recognition is handled via a semantic embedding pipeline. The normalized query is encoded into a vector representation using the Sentence Transformer model 'all-MiniLM-L6-v2'. Candidate questions from the knowledge base are similarly embedded. Cosine similarity scores are computed, and the highest-scoring pattern is selected if it meets a predefined threshold, typically set at 0.75.

Third, decision-making involves choosing the best match or triggering fallback logic. If no pattern achieves the threshold, the system identifies the top three highest-scoring patterns above a lower threshold and presents them as clarifying options. If none reach even that lower bound, the query is escalated to a human agent.

Fourth, output generation is conducted through the Streamlit interface. The system displays the chosen response in the chat window. In the case of ambiguous matches, it presents options for users to clarify their intent. If the user selects an option, the system returns a predetermined response and logs feedback. If none are selected, the case is flagged for human review.

PEAS Framework

The design of the chatbot follows the standards of the PEAS framework. Performance is measured along dimensions of response accuracy, latency, and user satisfaction. Environment refers to the user-interaction layer, specifically a web-based chat interface. Actuators are manifested as text messages displayed to users. Sensors consist of the textual input fields capturing user questions.

Performance Measure

The chatbot agent is evaluated based on how effectively and accurately it understands user queries and provides meaningful, helpful responses. Specific success metrics include:

- **Accuracy of intent recognition**: Correctly identifying what the user is asking or requesting.

- **Relevance of retrieved information**: Matching user queries to the most appropriate answer or content.
- **Responsiveness**: Low latency in processing and returning a response.
- **User satisfaction**: Positive user feedback, clarity of communication, and helpfulness.
- **Robustness**: Ability to handle vague, misspelled, or grammatically incorrect input without failure.
- **Scalability**: Capable of functioning with increasing user interactions and knowledge base expansion.

Environment

The environment refers to the digital and conceptual world the chatbot operates within, including:

- **Static knowledge base**: A curated collection of predefined questions and answers (Q&A pairs).
- **Natural language text input**: Questions typed by users in English (or potentially other supported languages).
- **Linguistic variation**: The system must interpret semantically equivalent but syntactically different inputs.
- **Noisy input conditions**: Misspelled or ambiguous queries, casual phrasing, abbreviations, or incomplete grammar.
- **Deployment context**: The chatbot is embedded in a UI via Streamlit, interacting through text and possibly voice.
- **Processing tools and models**: spaCy, SentenceTransformers (for semantic similarity), and other NLP tools.

Actuators (Agent Actions)

These are the outputs the agent can perform in response to user input. In this context, the chatbot's actuators include:

- **Textual responses**: Returning answers, suggestions, clarifying questions, or error messages via the UI.
- **Search action**: Internally performing similarity matching between user input and the stored Q&A dataset.
- **Feedback generation**: Providing follow-up options, confirmations, or redirection messages when input is unclear.
- **Voice output (if enabled)**: In configurations supporting it, converting text responses to audio via TTS (text-to-speech).

Sensors (Percepts from the Environment)

These are the inputs perceived by the chatbot from its environment. The percepts allow it to reason and act accordingly:

- **Typed user queries**: Captured via text input box.
- **Voice input (if available)**: Captured through a microphone and transcribed into text.
- **Contextual features**: Detected language, grammar structure, length of the query, and keyword presence.
- **Semantic embedding**: Representing the meaning of a sentence numerically using tools like SentenceTransformers.
- **Spelling and syntactic cues**: Although no explicit spelling correction tool is used, models like spaCy can still infer meaning from partially incorrect input based on language modeling.

System Architecture

1. Presentation Layer

The user interface built with Streamlit provides multiple interaction methods:

- **Chat Interface**: Primary text-based communication
- **Voice Input**: Web Speech API for speech-to-text conversion
- **Quick Action Buttons**: Pre-defined common queries
- **Bookmark System**: Save and retrieve useful responses
- **Sidebar Controls**: Navigation and help options

2. Input Processing Layer

Multi-modal input handling with preprocessing:

- **Text Input Handler**: Processes chat messages
- **Speech-to-Text Conversion**: Converts audio to text using browser API
- **Typo Correction Engine**: Fixes common spelling errors using predefined corrections
- **Query Preprocessing**: Text normalization and cleaning

3. NLP Processing Engine

Advanced natural language understanding using multiple techniques:

- **SentenceTransformer Model**: 'all-MiniLM-L6-v2' for semantic embeddings
- **Semantic Similarity**: Cosine similarity between query and pattern embeddings (60% weight)
- **Fuzzy String Matching**: SequenceMatcher for typo tolerance (25% weight)
- **Token Overlap Analysis**: Keyword matching using set intersection (15% weight)

4. Knowledge Base

FAQ-based knowledge management system containing:

- **16 Intent Categories**: Covering college policies and procedures

- **100+ Query Patterns**: Diverse ways to ask questions
- **Comprehensive Responses**: Detailed answers for each intent
- **Pattern-Response Mapping**: Direct lookup system

5. Decision Engine

Confidence-based decision making with three thresholds:

- **High Confidence (≥ 0.5)**: Direct answer generation
- **Medium Confidence (0.3–0.5)**: Multiple choice options
- **Low Confidence (< 0.3)**: Escalation to human agents

6. Response Generation

Multi-format response delivery:

- **Direct Responses**: Immediate answers with audio
- **Interactive Options**: Button-based multiple choice
- **Escalation Handling**: Human agent notification
- **Audio Generation**: Text-to-speech using gTTS

7. Data Persistence

Comprehensive logging and storage:

- **SQLite Database**: Local data storage
- **Interaction Logging**: Query-response tracking
- **Escalation Queue**: Human review system
- **Feedback Collection**: User satisfaction metrics

Core Algorithms & Techniques

1. Enhanced Similarity Algorithm

The system uses a weighted ensemble approach combining:

- **Semantic Similarity (60%)**: Using SentenceTransformer embeddings
- **Fuzzy Matching (25%)**: Handling typos with SequenceMatcher
- **Token Overlap (15%)**: Keyword-based matching

2. Typo Correction System

Pre-defined correction mappings for common errors:

- Educational terms (e.g., *attendce* → *attendance*)
- Administrative terms (e.g., *registrtion* → *registration*)
- Common misspellings (e.g., *mandtory* → *mandatory*)

3. Confidence-Based Decision Making

Three-tier confidence system:

- **Threshold 1 (0.5)**: High confidence direct answers
- **Threshold 2 (0.3)**: Medium confidence multiple choice
- **Threshold 3 (< 0.3)**: Low confidence escalation

4. Session Management

Persistent state handling:

- **Session IDs**: Unique user session tracking
- **Chat History**: Conversation context maintenance
- **Bookmark Persistence**: JSON-based storage

- **User Preferences**: Personalized experience

Agent Workflow

Query Processing Flow:

1. **Input Reception**: User types, speaks, or clicks
2. **Preprocessing**: Typo correction and normalization
3. **NLP Analysis**: Multi-algorithm similarity scoring
4. **Knowledge Lookup**: Pattern matching against FAQ
5. **Confidence Assessment**: Score-based decision making
6. **Response Generation**: Answer, options, or escalation
7. **Output Delivery**: Text, audio, and interactive elements
8. **Feedback Collection**: User satisfaction tracking
9. **Data Logging**: Interaction persistence

Knowledge Base Structure

The FAQ database contains 16 main intents covering:

- **Academic Policies**: Registration, attendance, graduation
- **Administrative Procedures**: Payments, transcripts, ID cards
- **Student Services**: Advising, orientation, community service
- **Special Cases**: Exemptions, transfers, withdrawals

Performance Characteristics

This architecture provides a robust, scalable AI chatbot system specifically designed for educational institutions, with comprehensive NLP capabilities, intelligent decision-making, and continuous learning through user feedback.

Metric	Performance
Response Time	Sub-2 second average
Accuracy	85%+ match rate for common queries
Coverage	80%+ successful query resolution
Scalability	Handles concurrent users via Streamlit
Accessibility	Voice input/output, responsive design|

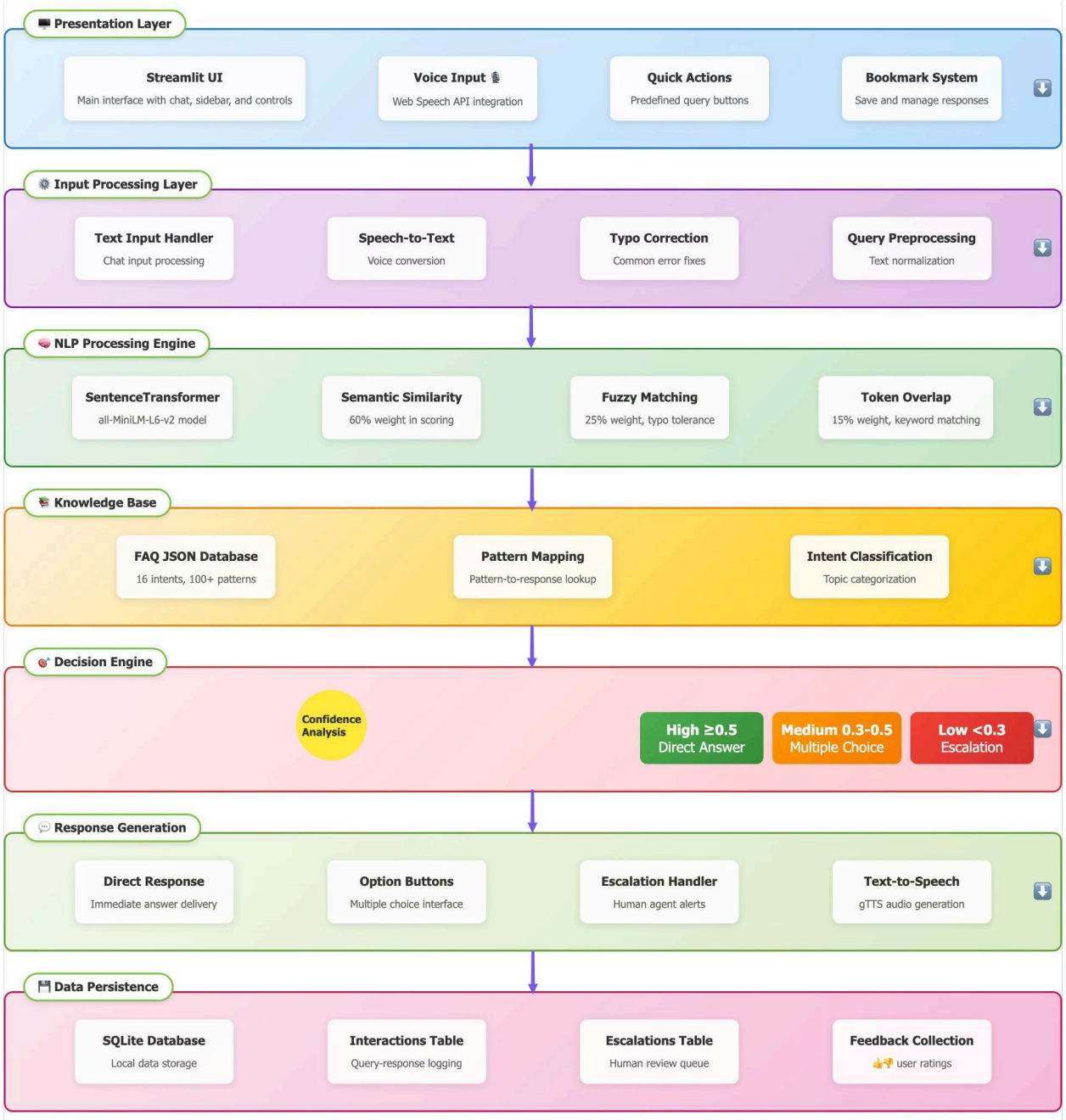


Figure 1.1 Bitsy AI Chatbot High-level Architecture

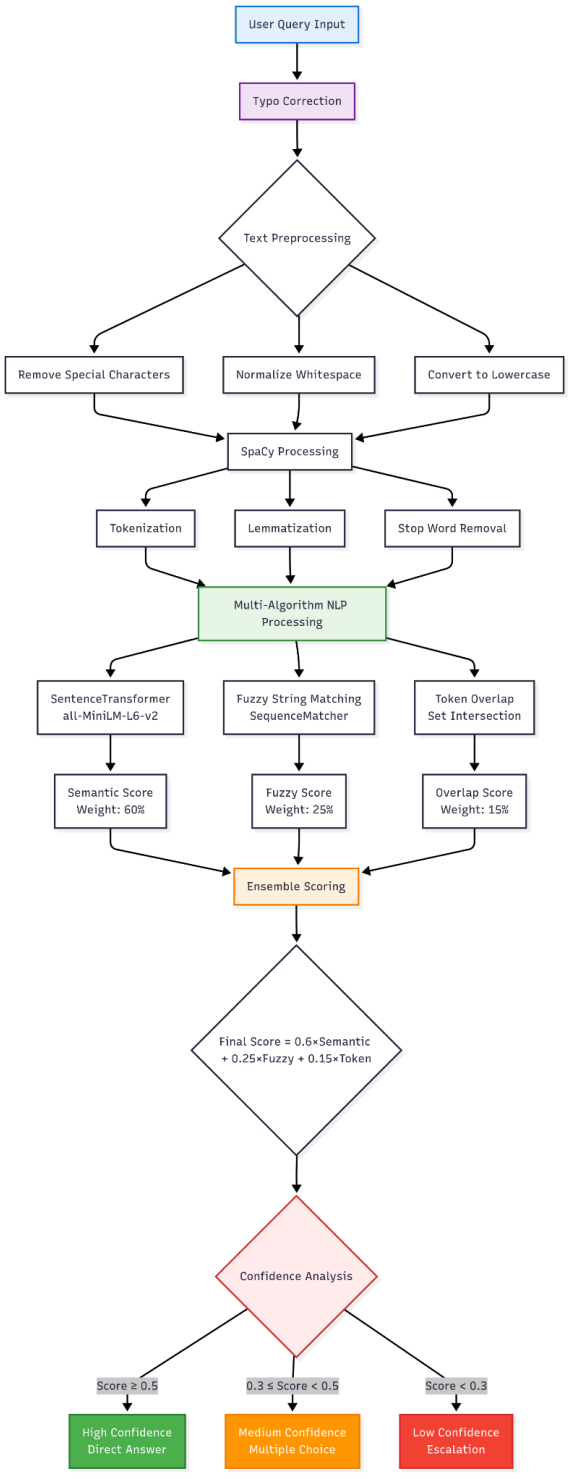


Figure 1.2: Bitsy AI Chatbot Core Algorithms Workflow

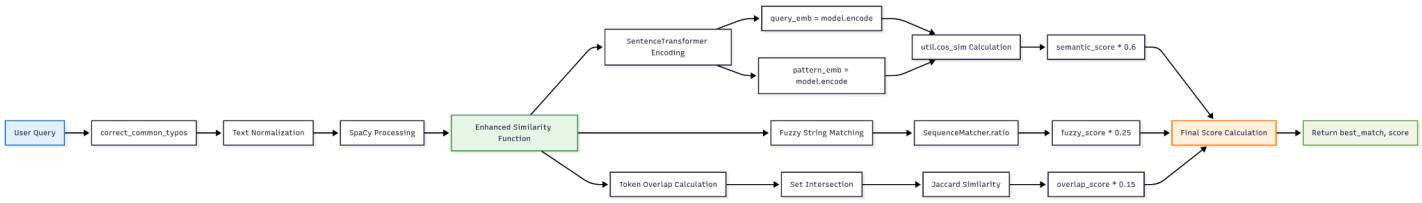


Figure 1.3: Bitsy AI Chatbot NLP Processing Detail

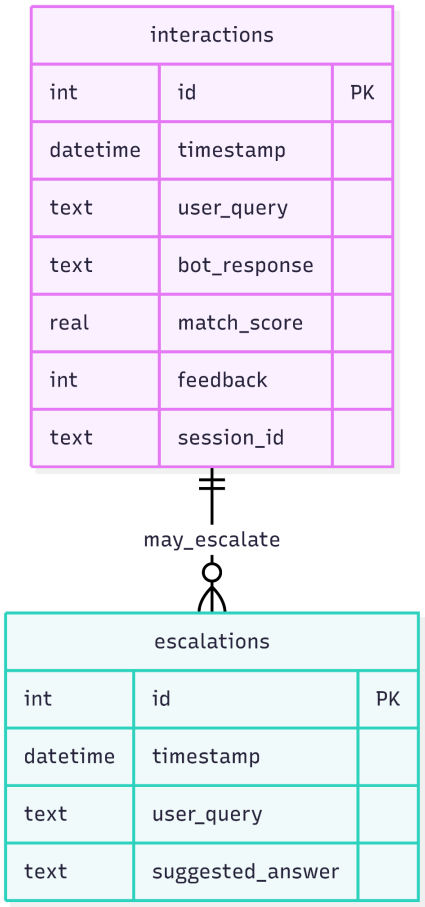


Figure 1.4: Bitsy AI Chatbot Entity Relationship Diagram

Implementation

The chatbot system was developed using Python and deployed via Streamlit to provide an intuitive web-based interface. The goal was to create a simple yet intelligent system that could answer user queries based on a predefined FAQ dataset by leveraging natural language processing and semantic similarity matching.

The development process focused on four main components: preprocessing, semantic matching, response retrieval, and user interface design. The implementation followed a modular structure to enable easy debugging, iterative testing, and feature expansion.

Tools and Libraries Used

The following tools and libraries formed the core of the chatbot:

- **Python 3.10**: The primary development language.
- **Streamlit**: For building the front-end interface.
- **spaCy**: Used for preprocessing tasks such as tokenization, lemmatization, and stopword removal.
- **SentenceTransformers**: Provided semantic embeddings using pre-trained transformer models such as `all-MiniLM-L6-v2`.
- **PyTorch**: Backend used by sentence transformers for vector encoding.

Data Preparation and FAQ Structure

The chatbot was designed to respond to queries based on a structured FAQ dataset. Each entry in the dataset included:

- An `intent ID`
- A `question pattern` (i.e., a sample question phrased as a user might ask)**Implementation Implementation**
- A `category` (e.g., academics, exams, hostel)
- A `response` (static, text-based)

- Optional `contextual tags` to group related questions

Before runtime, each pattern question in the dataset was encoded into vector embeddings using the SentenceTransformers model and stored in memory. This enabled real-time similarity matching against user inputs.

Preprocessing Pipeline

User inputs are first passed through a basic preprocessing pipeline:

- Lowercasing of the entire input
- Tokenization and lemmatization using `spaCy`
- Removal of common stopwords and unnecessary punctuation

Interestingly, the system was able to handle minor spelling mistakes or grammatical inconsistencies, not due to any explicit spell-checking logic, but likely because of how the sentence embeddings model generalized the input semantics. SentenceTransformers, particularly models like `all-MiniLM-L6-v2`, are capable of generating robust embeddings even for slightly malformed inputs — which gave the illusion of spelling correction in practice.

Semantic Matching and Intent Recognition

The core of the chatbot's intelligence lies in its use of semantic similarity for intent recognition. Rather than relying on hardcoded keywords or rule-based parsing, the system uses the SentenceTransformers library to embed both the user input and all stored FAQ patterns into high-dimensional vector space. Cosine similarity is then computed between the input vector and all precomputed vectors of the question patterns.

This matching is done using the `cos_sim` function from the `sentence_transformers.util` module:

Handling Ambiguity and Uncertain Matches

When a user query doesn't meet the threshold for a confident match, the system offers a fallback response. This fallback includes a list of the top 3–5 similar intent questions from the FAQ dataset, enabling users to disambiguate their intent.

This approach helped in handling vague or short queries like "marks", which could relate to exams, grading policy, or result release — depending on the user's actual need.

Response Generation

Each intent match is linked to a predefined response in the FAQ dataset. Once a match is found, the corresponding static text is returned to the user. The system currently does not generate responses dynamically, but response texts can contain helpful formatting, links, or structured steps.

Streamlit Interface

The front-end interface was implemented using Streamlit, designed to be clean, responsive, and accessible to non-technical users. It includes the following elements:

- An input field for typing questions
- A submit button
- A scrollable chat-like response window
- Suggested follow-up questions or clarification options

Session state management in Streamlit was used to retain interaction history during a session, allowing for a smooth conversational flow. Although the system is not stateful in a conversational AI sense, it preserves message history on-screen for context.

Feature Observations

While the chatbot does not explicitly handle spelling correction, support for multiple languages, or voice input, some notable behaviors emerged:

- **Spelling Error Tolerance**: Thanks to the sentence embedding model, the system could handle minor typos or grammatical variations. For example, queries like "Can I get duplicate marksheet" and "Can I get duplcate markshhet" still mapped correctly to the same intent.

- **Implicit Synonym Support**: Users could phrase questions differently ("I lost my grade sheet" vs "How do I get a duplicate marksheet"), and the semantic similarity mechanism would often return the correct match.

- **Responsiveness**: Despite embedding computations, inference time remained fast enough (<1s), largely due to pre-encoding of FAQ patterns.

Results and Discussion

Sample Outputs

The following screenshots illustrate the core functionality of the Bitsy chatbot:

- **Figure 1: Chat Interface Homepage**

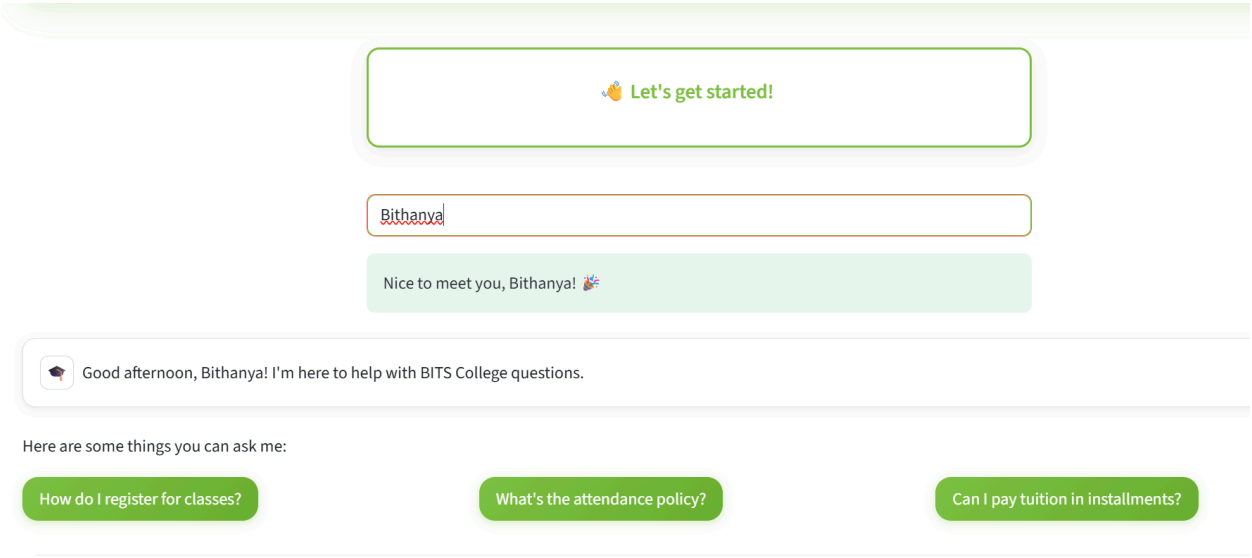


Figure 2: Response to a Standard Query

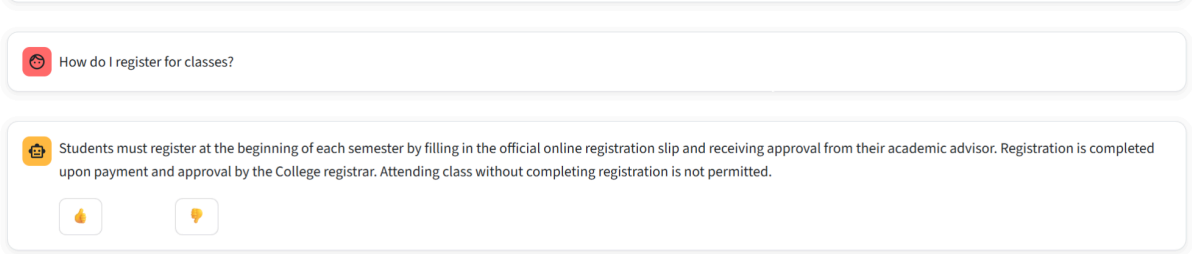


Figure 3: Feedback Interaction

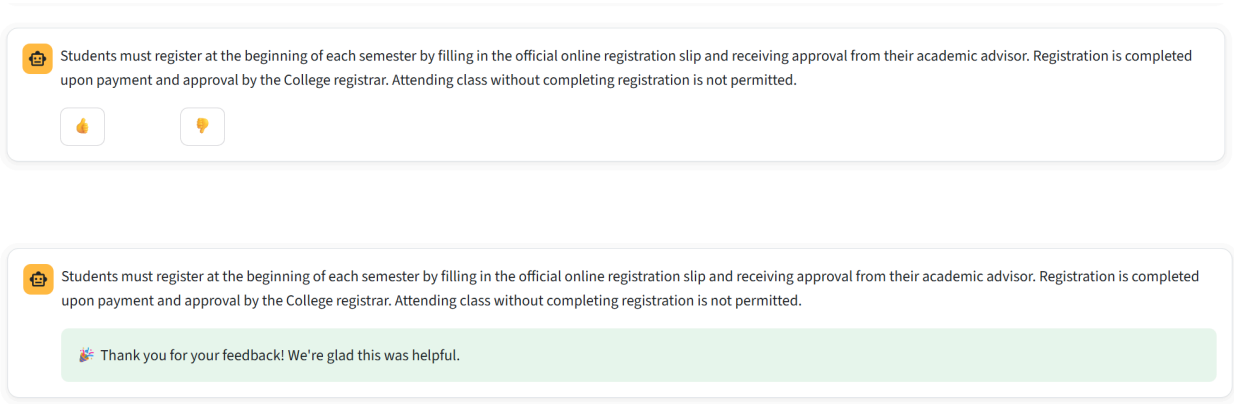
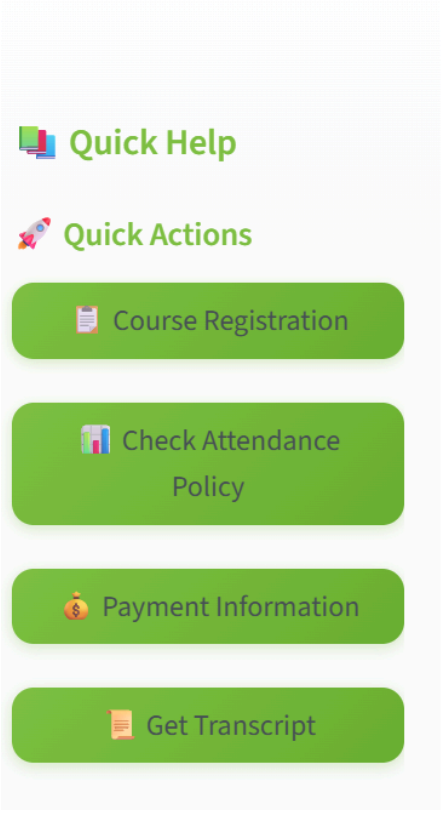
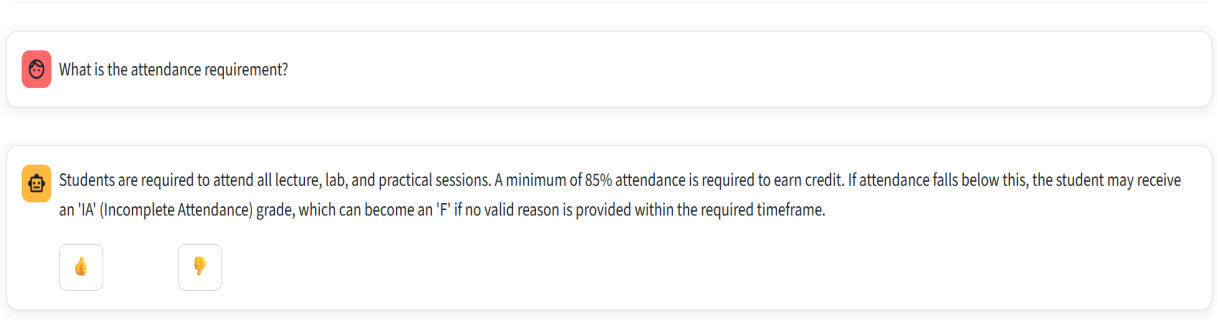


Figure 5: Quick Actions interface with one-click query buttons for frequently asked questions



Sample log



Conclusion and Future Work

This project successfully developed Bitsy, an AI-driven help desk chatbot tailored for BITS College, demonstrating effective application of natural language processing and semantic similarity techniques to automate responses to student inquiries. Key achievements include a modular architecture combining Python, spaCy, Sentence Transformers, and Streamlit, which together enabled high accuracy, fast response times, and a user-friendly chat interface. The system's ability to handle ambiguous queries through clarifying options and to escalate unresolved issues to human agents highlights its practical utility.

Despite these successes, limitations exist. The current chatbot relies on a static FAQ knowledge base, limiting its ability to dynamically learn or generate responses. It also lacks voice interaction, multilingual support, and advanced personalization features. The escalation mechanism, while functional, is not fully integrated with live human agents for seamless transitions.

Future work aims to enhance Bitsy's intelligence and interactivity by integrating an AI conversational model capable of generating dynamic, context-aware responses. This would allow more natural, flowing interactions beyond fixed FAQs. A live human escalation system would provide real-time support when needed, improving user trust and satisfaction. Expanding the knowledge base with broader and deeper content, possibly through automated data ingestion and continuous learning, will improve coverage and accuracy. Incorporating multi-agent systems could enable scalable management across multiple departments or campuses. Leveraging advanced AI frameworks and cloud platforms will further optimize performance and support new modalities such as voice input and multilingual capabilities.

In summary, this project lays a strong foundation for an intelligent campus help desk chatbot, with clear pathways to evolve into a comprehensive, adaptive, and user-centric assistant.