



TECHNISCHE UNIVERSITÄT
CHEMNITZ

Fakultät für Informatik

CSR-25-05

Development of a Retrieval Model based Backend of a Tutoring Agent

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August 2025

Chemnitzer Informatik-Berichte



TECHNISCHE UNIVERSITÄT
CHEMNITZ

Development of a Retrieval Model based Backend of a Tutoring Agent

Master Thesis

Submitted in Fulfilment of the
Requirements for the Academic Degree
M.Sc.

Dept. of Computer Science
Chair of Computer Engineering

Submitted by: Ambu Babu

Student ID: 672210

Date: 13.08.2024

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Abstract

In today's rapidly evolving educational landscape, the need for interactive, accessible, and efficient learning tools has become increasingly paramount. Traditional methods of instruction often face limitations in providing personalized and immediate assistance to students, which can hinder their learning experience. This study proposes the development of an interactive web-based system designed to assist students by answering their questions and providing emotional engagement through an avatar interface. The system, implemented using Python, combines the functionalities of two primary models: the ChatterBot model for generating replies and the TextBlob model for performing sentiment analysis. The ChatterBot model was trained to respond accurately to a wide range of student inquiries, while the TextBlob model was utilized to detect and interpret the emotional tone of the students' inputs. A web application was built, and the sentiment analysis capability allows an avatar in the web page of the web application to display appropriate emotions, enhancing the interactive experience and making the system more relatable and engaging for students. The system was able to generate relevant and coherent replies based on student inputs and effectively perform sentiment analysis. The implementation of this system shows significant promise in the educational field by offering a resource for students to resolve their queries independently, thereby reducing reliance on teacher intervention and fostering a more autonomous learning environment. The successful development and deployment of this interactive educational system confirm that the objectives of the study have been achieved.

Keywords: Retrieval model, ChatterBot, TextBlob, Sentiment Analysis, Avatar.

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1 Introduction

The advent of artificial intelligence (AI) has significantly transformed various sectors, marking a pivotal shift in how industries operate and interact with technology. Since its full-fledged introduction, AI has permeated major industries, driving innovation and enhancing operational efficiency. In education, for instance, AI's impact is particularly pronounced, as intelligent systems are increasingly utilized to create personalized learning experiences. These systems can engage in real-time conversations with students, addressing their queries and providing tailored support. Notably, Intelligent Tutoring Systems (ITS), proposed by Sleepman and Brown in 1982, exemplify this shift by mimicking human instructors and delivering individualized instruction based on students' knowledge and preferences.

Furthermore, AI techniques such as machine learning enable the detection of emotions in text, enriching the educational experience by allowing for more nuanced interactions. By analyzing online learners' behaviors and characteristics, ITS facilitate real-time personalized learning guidance and resource recommendations, fostering an adaptive learning environment that meets the diverse needs of students. As AI continues to evolve, its integration into education and other industries promises to redefine traditional models, paving the way for more efficient and effective practices across the board.

1.1 Motivation

The rapid evolution of educational technology has introduced numerous tools designed to enhance learning experiences, among which Intelligent Tutoring Systems (ITS) have gained significant traction. These systems, powered by advanced algorithms and machine learning, offer personalized learning guidance, resource recommendations, and adaptive educational paths that cater to the unique needs of individual students. The significance of such intelligent tutoring in modern education cannot be overstated. Well-designed intelligent agents engage and motivate students, provide interactive and guided help, and produce higher levels of satisfaction among learners. Moreover, the immediate feedback and visualization capabilities embedded in these systems foster a more engaging and effective learning environment. However, despite these

advancements, a critical gap remains: the lack of emotional intelligence in existing chatbot systems. Addressing this gap is the primary motivation for this study.

A survey data from a big sample (n = 5894) across Swedish universities to explore students' perceptions and adoption of ChatGPT and other chatbots based on AI in higher education. Descriptive statistical methods were employed to analyze concerns, attitudes and usage while inferential statistics were used to identify relationships between attitudes, background variables and usage such as, field of study, academic level and gender. The findings revealed broad awareness and use of ChatGPT among students, with over half expressing positive attitudes towards chatbot use in education. However, significant differences were observed across gender and fields of study, with female students and those from the medicine and humanities showing more negative attitudes and concerns compared to males and students in technology and engineering [1].

Incorporating Artificial Emotional Intelligence (AEI) into chatbot systems presents a promising solution to E-learning. AEI aims to endow chatbots with the ability to interpret and respond to human emotions, thereby enhancing the quality of interactions between students and these digital assistants. Leveraging Natural Language Processing (NLP) and Machine Learning (ML) technologies, AEI can enable chatbots to analyze student sentiments and emotions expressed through text. This ability to understand and respond to emotional cues can transform chatbots from mere information retrieval tools into empathetic and supportive educational companions. By developing a retrieval-based chatbot capable of detecting and interpreting emotions, the study aims to create a more holistic and supportive learning environment. Such a chatbot would not only provide accurate responses to academic queries but also offer emotional support, thus addressing the dual needs of knowledge acquisition and emotional well-being. This dual functionality is particularly important in educational settings where students often face stress, anxiety, and frustration. An emotionally intelligent chatbot can recognize these states and offer appropriate support or direct students to additional resources, thereby enhancing their overall educational experience. The backend development of this advanced chatbot includes several key features designed to enhance its utility and effectiveness. The chatbot will provide responses to queries, allow students to select

from predefined options, and retrieve data from a learning analytics dashboard. This integration with learning analytics will enable the chatbot to offer personalized recommendations and insights based on individual student behaviors and characteristics. By analyzing data on student interactions and performance, the chatbot can tailor its responses and support to better meet the needs of each learner.

The motivation for this study is driven by the need to bridge the gap between technical assistance and emotional support in educational chatbots. By integrating ML technologies, this study aims to create a chatbot that not only resolves academic queries but also recognizes and responds to the emotional states of students. This approach has the potential to significantly enhance student engagement, satisfaction, and overall learning outcomes. Through this research, the study aspires to contribute to the development of more empathetic and effective educational technologies that can better support the diverse needs of modern learners.

1.2 Problem statement

In the contemporary educational landscape, Intelligent Tutoring Systems (ITS) and chatbots have emerged as crucial tools for enhancing student engagement and learning outcomes. These systems offer personalized learning guidance, immediate feedback, and interactive assistance, contributing significantly to students' academic success. However, a critical limitation persists: the lack of emotional intelligence within these chatbots. Despite their efficiency in resolving technical and informational queries, current chatbot systems are ill-equipped to interpret and respond to the emotional and psychological needs of students. This deficiency in emotional intelligence represents a significant gap in the potential of chatbots to provide holistic educational support. While chatbots can efficiently address questions about coursework and offer resource recommendations, their inability to recognize and respond to students' emotional states can lead to interactions that feel impersonal and unsupportive. This lack of empathy can negatively impact student engagement, satisfaction, and overall well-being, especially in stressful or challenging academic situations. The role of Artificial Emotional Intelligence (AEI) in addressing this gap is crucial. By leveraging Natural Language Processing (NLP) and Machine Learning (ML) technologies, AEI can enable chatbots to detect and interpret student sentiments and emotions, thereby enhancing

the quality of interactions. Integrating AEI into chatbots can transform them from mere information retrieval tools into empathetic digital companions capable of providing both academic and emotional support.

1.3 Objectives

The main objectives of the study are as follows:

1.3.1. Prepare the Dataset for Training the Chatterbot

The first objective involves creating and curating a comprehensive dataset that contains predefined queries and corresponding responses. This dataset serves as the foundational training material for the Chatterbot, ensuring it has a wide range of conversational examples to learn from. The dataset needs to be diverse and representative of the types of interactions the chatbot is expected to handle.

1.3.2. Train the Chatterbot Using the Prepared Dataset

Once the dataset is ready, the next step is to train the Chatterbot using this data. This involves inputting the dataset into the Chatterbot framework, which will use machine learning algorithms to understand patterns, context, and appropriate responses. The training process is crucial as it determines the accuracy and relevance of the Chatterbot's responses in real-world scenarios.

1.3.3. Test the Chatterbot to Ensure Accurate Responses

After training, the Chatterbot must be rigorously tested to verify that it can generate accurate and contextually appropriate responses. This testing phase includes running various queries and scenarios through the Chatterbot to identify any errors or areas where the responses may be inadequate. The goal is to refine the system to a point where it can reliably perform in a live environment.

1.3.4. Implement Sentiment Analysis Using TextBlob

To enhance the Chatterbot's capabilities, the study integrates sentiment analysis using TextBlob, a natural language processing (NLP) tool. This step involves analysing the emotional tone of the user's input, allowing the Chatterbot to respond in a manner that is not only contextually correct but also emotionally intelligent. The sentiment analysis

ensures that the chatbot can adjust its responses based on the detected sentiment, such as replying more empathetically to a user expressing frustration.

1.3.5. Integrate the Chatterbot and Sentiment Analysis with a Web Application

The final objective is to deploy the Chatterbot, along with the sentiment analysis feature, within a web application. This integration allows users to interact with the Chatterbot through a user-friendly interface, ensuring seamless communication. The web application serves as the platform where the chatbot operates, providing users with real-time responses that are both contextually relevant and emotionally aware.

2 Fundamentals

Chatbots are software applications that utilize natural language processing (NLP) to simulate human conversation, providing users with real-time responses to their queries. They can be categorized into two main types: retrieval-based and generative chatbots. Retrieval-based chatbots rely on a predefined set of responses stored in a database, retrieving the most relevant answer based on user input. This ensures consistent and accurate responses but limits flexibility in handling novel queries. In contrast, generative chatbots use machine learning models to create responses dynamically, allowing for more engaging interactions but potentially leading to inconsistencies. NLP is a critical component of chatbot technology, encompassing techniques such as tokenization, part-of-speech tagging, named entity recognition, and sentiment analysis, which enable machines to understand and interpret human language. Chatbots have a wide range of applications across various industries, including customer support, e-commerce, healthcare, and education, where they enhance user experience and operational efficiency. Understanding these fundamentals provides a foundation for exploring specific chatbot types, libraries, and techniques in greater detail.

2.1 Retrieval-based chatter bot

The theory behind retrieval-based chatbots revolves around the concept of utilizing a pre-existing database of responses to address user queries. Unlike generative models that create new text on the fly, retrieval-based chatbots operate by matching user inputs to stored queries and their associated responses [59]. When a user submits a question, the system processes this input using natural language processing (NLP) techniques to understand its intent. It then compares the processed input to a database of predefined responses using similarity metrics such as cosine similarity or more sophisticated methods like word embeddings. The chatbot selects the most relevant response based on this comparison. This approach ensures consistent and controlled interactions, as the responses are predetermined. However, it has limitations, including a lack of flexibility in handling novel queries and challenges in managing context over longer conversations. Overall, while retrieval-based chatbots offer reliability and simplicity, they are constrained by their reliance on predefined content.

2.2 Chatterbot library

The ChatterBot library for Python is designed to facilitate the creation of chatbots through natural language processing and machine learning techniques [60]. The core idea behind ChatterBot is to enable chatbots to generate responses based on past interactions and patterns learned from training data. The library uses machine learning algorithms to analyze a corpus of conversation data, allowing the chatbot to understand language nuances and context. It then generates responses by applying statistical models that evaluate the probability of different replies based on previous conversations. ChatterBot also includes various adapters to handle response generation and can maintain simple conversational context through its history. Its straightforward API makes it easy for developers to set up and train chatbots, while its adaptability allows the chatbot to improve over time as it encounters new inputs. However, it may struggle with more complex interactions due to limited context management and reliance on statistical methods, potentially requiring additional customization for advanced applications.

2.3 Textblob library

The TextBlob library for Python is a versatile tool that simplifies natural language processing (NLP) tasks, making it accessible for users working with text data [61]. It provides an intuitive interface for performing common tasks such as sentiment analysis, where it assigns polarity and subjectivity scores to evaluate the emotional tone and objectivity of the text. TextBlob also excels in part-of-speech tagging, which helps in understanding the grammatical structure of the text by labeling words with their respective parts of speech. Additionally, the library can extract noun phrases, making it easier to identify key topics within the content. Its support for translation and language detection enhances its utility in multilingual applications. TextBlob also includes features for text normalization, such as tokenization and lemmatization, and can correct spelling errors. While its simplicity and broad range of functionalities make it ideal for quick and basic text analysis, it may not handle more complex NLP needs as effectively as advanced libraries like SpaCy or NLTK. Overall, TextBlob is a valuable tool for straightforward text processing and analysis, though it might be limited for more specialized tasks.

2.4 Sentimental analysis

Sentiment analysis is a technique in natural language processing that involves determining the emotional tone behind a piece of text [62]. The primary goal is to classify the sentiment expressed in the text as positive, negative, or neutral. This process typically involves analyzing the text's language and structure to assign a sentiment polarity score, which quantifies the overall sentiment. A positive score indicates a positive sentiment, such as happiness or excitement, while a negative score suggests negative emotions like sadness or frustration. A neutral score represents a lack of strong emotional tone. By mapping these scores to specific emotions, sentiment analysis can provide insights into the emotional state or attitudes expressed in the text. This method is widely used in various applications, such as analyzing customer feedback, monitoring social media, and understanding public opinion, allowing businesses and researchers to gauge the emotional responses of individuals and groups.

3 State-of-the-Art

The state of the art in chatbot design involves the integration of various advanced techniques to create more intelligent and responsive conversational agents. Traditional methods such as pattern matching and AIML (Artificial Intelligence Markup Language) remain widely used due to their simplicity and effectiveness in managing structured interactions. However, recent advancements have introduced more sophisticated approaches, including natural language processing (NLP) techniques like parsing and deep learning models such as LSTM (Long Short-Term Memory) networks. These methods enable chatbots to better understand and process user inputs, offering more personalized and contextually relevant responses.

Additionally, open-source frameworks like RASA have gained popularity due to their flexibility and robust features, such as reinforcement learning and policy-based decision-making. The use of these techniques has expanded the application of chatbots across various industries, enhancing customer service, education, and healthcare. Despite these advancements, challenges remain, particularly in improving emotional intelligence, handling complex language variations, and learning from previous interactions to reduce repetitive responses. Continued research and development are crucial for overcoming these limitations and further advancing the capabilities of chatbots.

3.1 Design and Techniques Used for Chatbots

The design techniques used in developing chatbots, including pattern matching, AIML, language tricks, Chatscript, parsing, SQL and relational database, and Markov Chain which were proposed in this study by [2]. The data for the study consists of various examples of chatbots, such as Chat.io, Collect.chat, and Cleverbot, which are used to illustrate the different design approaches. Additionally, the study provides a background on chatbot systems, their usage in various fields like education, healthcare, and business, and the general process of how chatbots work. The results of the study suggest that the most popular techniques used by developers are pattern matching, where the bot matches phrases to keywords in a pre-specified dictionary, and AIML, a markup language that directs the conversational modeling into a stimulus-response process. The study also discusses the advantages and challenges of

designing and implementing chatbots, highlighting the importance of careful planning, choosing appropriate platforms and tools, and staying up-to-date with the rapidly evolving chatbot technology. The limitations of the study include the lack of a comprehensive evaluation of the performance of the different chatbot design techniques, as well as the absence of a comparative analysis of the effectiveness of the various approaches in specific application domains. Overall, the study provides a valuable review of the current state of chatbot design techniques, which can serve as a reference for researchers and practitioners interested in developing intelligent conversational systems.

The development of chatbots using natural language processing (NLP) techniques was implemented in this study by [3]. The data used in the study included various datasets such as Stanford CoreNLP, Cancer forums, and MHMC chitchat (Chinese). The study also employed additional methods, including intent classification using convolutional neural networks, AIML (Artificial Intelligence Markup Language), and LSTM (Long Short-Term Memory) for multilayer processing to extract semantic and relationship details between sentences. The results indicate that the use of these NLP techniques, such as pattern matching, parsing, and deep learning, can enable chatbots to effectively communicate with users, provide personalized responses, and handle a wide range of queries. The study also highlighted the limitations of the current chatbot systems, including the need for improved emotional intelligence, better handling of grammatical errors, and the ability to learn from previous conversations to avoid repetitive responses. The study suggests that the continued development and refinement of NLP-based chatbots can significantly enhance the user experience and provide more efficient and intelligent customer service solutions across various industries.




Analyzing the open-source chatbot framework, RASA, and its various features was discussed in this study by [4]. The data for the study consists of the RASA framework, including its two main components, RASA NLU and RASA Core, as well as the implementation details of RASA, such as interaction with databases, APIs, conversational flow, and interactive learning with reinforcement neural networks. The

study also examines the Tracker Store, which maintains the conversation state, and the modification of the socket.io core file to capture the user's IP address and port. Additionally, the study explores the various policies, such as MemoizationPolicy, MappingPolicy, KerasPolicy, and TEDPolicy, used in RASA Core to decide the appropriate next action during a conversation. The results of the study indicate that the combination of these policies, along with the proper configuration of parameters like Max_History and Data Augmentation, can lead to the best performance of the RASA model. The study also highlights the advantages of RASA over other enterprise software, such as its extensibility and open-source license, which make it a versatile choice for chatbot development.

3.2 Application Based Chatbots

The study employed a 2 (platform: web vs. chatbot) × 2 (conversational style: formal vs. casual) between-subjects experimental design to explore the feasibility of a text-based virtual agent as a new survey method which was discussed in this study by [5]. The data consisted of responses from 117 adolescent participants, who were randomly assigned to one of the four conditions. The study also used qualitative methods, including thematic analysis of open-ended responses from the chatbot survey participants, to gain deeper insights into their perceptions and experiences. The results showed that the chatbot survey participants were less likely to exhibit satisficing behavior, as measured by the differentiation response index, compared to the web survey participants. This effect was more pronounced when the chatbot survey used a casual conversational style. However, the survey platform and conversational style did not have a significant impact on the participants' perceived ease of use. The study's findings suggest that a chatbot survey with an appropriate conversational style can enhance survey response quality by increasing respondent engagement. A key limitation is that the study focused on adolescent participants, and the findings may not generalize to other age groups or contexts. Additionally, the study did not address potential issues related to the "gulf of execution," where users' relational expectations towards the chatbot may not be met, leading to disappointment.

Table 1: Comparison of Various Chatbot Software Tools

Chatbot Software Tools	Best For	Features	Cost Effectiveness
Mitsuku/Kuki	entertainment-focused chatbot	based on the AIML (Artificial Intelligence Markup Language) technology.	Not open source, Licensed by Pandorabots
Botpress 	various practical applications	build chatbots using visual flows and small amounts of training data.	Open source
Botsify 	corporate or education settings	Integrate with a website, Facebook, Amazon, and Slack	Not open source 14-day free trial
ChatterBot 	various practical applications	machine learning, conversational dialog engine for creating chatbots.	Open source

A retrieval-based approach for developing a college enquiry chatbot using sentence similarity was proposed in this study by [6]. The main method involves tokenizing the user's input, processing the tokens using a normalizer and matcher, and retrieving the most appropriate response from a pre-defined dataset based on a calculated similarity score as shown in figure 1. The dataset used in this study consists of college-related information such as facilities, procedures, and policies. To evaluate the performance of the chatbot, the study conducted a questionnaire-based survey that assessed parameters like, accessibility, effect, humanity and performance. The results show that the web application incorporating the chatbot exhibited a 20% enhancement in performance and a 5% improvement in accessibility compared to the existing website. Additionally, the study found that the chatbot's humanity and affect reached an average level, indicating room for improvement in maintaining natural conversations. The retrieval-based approach demonstrated the feasibility of developing a college enquiry chatbot that can enhance the user experience and reduce the workload of the organization.

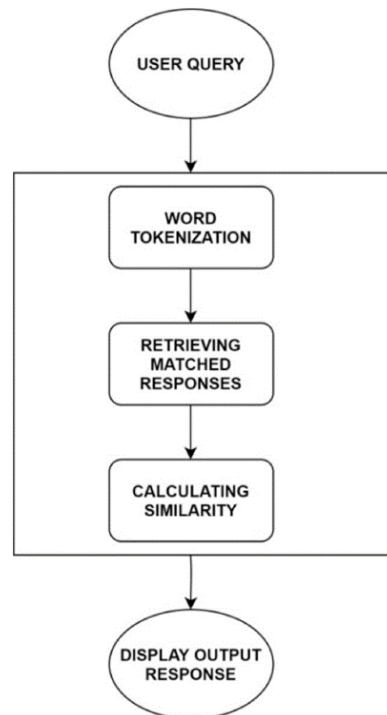


Figure 1: College enquiry chatbot system design [6]

ChatbotSQL, a conversational agent to support the learning of the SQL language for database querying was in an autonomous manner developed in this study by [7]. The data used in the study consisted of 24 query exercises defined by the lecturers, ranging from beginner to advanced levels, which were solved by 64 students, resulting in a total of 2,226 attempts. The study also used three MySQL databases: a System Database to store the platform data, and two Testing Databases to run and compare the students' queries with the solution queries. Additionally, the study used IBM Watson Assistant to process all the messages received from the students. The analysis of the student-chatbot interaction showed a high accuracy, with precision, recall, and F1-scores higher than 80% for most of the keywords. The results of the student evaluation revealed a positive perception of the usefulness of ChatbotSQL, particularly in supporting the resolution of nested and join queries, with 65.5% and 68.9% of the students agreeing or strongly agreeing, respectively. Furthermore, the quasi-experiment conducted in the study suggested a possible improvement in student performance, with 90.6% of the students who used ChatbotSQL passing the SQL exam, compared to 80.37% of the total students. However, the study acknowledges

the need for further research in other contexts to confirm the effectiveness of ChatbotSQL in improving SQL learning.

A web-based chatbot named Hebron for the Covenant University Community Mall utilizing MySQL as the database to structure the e-commerce datasets and Admin Portal process, and React.js and Python as the programming languages, was implemented in this study by [8]. The e-commerce chatbot application for Covenant University Shopping Mall (CUSM) aimed to provide a smart, easy, comfortable shopping experience and easy for the Covenant University Community. The study involved designing a web page where the chatbot would be deployed using React, developing the chatbot with datasets and deep Natural Language Processing (NLP), creating a database of items currently available at the shopping mall, introducing administrator privileges to update the list of items that are currently available and the number of stocks associated with each item, and system testing to ensure the proper functionality of the chatbot that is built, alongside user testing by a group of people to provide constructive feedback on the developed chatbot. The results showed that the chatbot interface and functionality were rated as good and satisfactory by 60% and 50% of the users, respectively, and 60% of the users believed that the chatbot fulfilled its functionalities. Additionally, all the testers (100%) believed that Hebron was highly recommendable. The study suggests that more features can be integrated into the chatbot, such as the delivery of items that have been paid previously to student halls of residence, more phrases associated with training can be added to the chatbot to give it an improved social outlook, and the addition of items to the chatbot database done in an automated manner, for example, incorporating an option to read the barcode to the chatbot.

A rule-based smart tourism chatbot using the Neo4J graph database was developed in this study by [9]. The main method employed in the study was the use of a morpheme analyzer, specifically the khaiii (Kakao Hanguk Analyzer III), along with a proper noun dictionary containing tourist destination names and a general noun dictionary including frequently used words in tourist information search, to understand the intention of the user's question. The study utilized more than 1,300 Jeju tourism

information used in the smart tourism app to create the tourism knowledge base in the Neo4J graph database. The study also created dictionaries to correct typos and spacing in user's question sentences, as well as an error patch dictionary to prevent misanalysis by the khaiii morpheme analyzer. The study developed the tourism knowledge base by adding service attribute data, such as information on tourist companions and popular tourist attractions, to the existing tourism information. The study then used the properties of nodes and relationships in the Neo4J tourism graph database to provide answers to tourists' questions. While the study did not compare the performance of different models, it demonstrated the effectiveness of the rule-based approach using the Neo4J graph database in providing personalized tourism information to individual tourists through the smart tourism chatbot.

A web-based chatbot framework developed using various machine learning and natural language processing techniques to manage frequently asked queries (FAQs) in hospitals was employed in this study by [10]. The main method employed in the study involves integrating the bot engine with several machine learning approaches such as natural language processing (NLP) and gradient descent (GD) algorithms. The trained data given as input into the bot were separated into mini-word batches, and the GD algorithm was applied in a sequential manner on each mini-batch. The NLP methods involve transforming a word to its stem with a text result which is in a less readable form by humans. Additionally, the study incorporated text classification algorithms along with the GD to evaluate better outcome responses. The results show that the employed ML algorithms were successfully incorporated to manage the alternative synchronization of text and voice messages. The proposed bot can be an enhanced solution for extracting data from local hospitals, functioning as a good communication channel for both hospital staff and users, and helpful in lessening the crowd. The model developed in the study exhibited 100% accuracy from the 393rd iteration step for the chatbot trained for approximately 1000 epochs, and the loss function consistently declined till the last iteration, proving the efficiency of the chatbot model.

3.3 Advanced Techniques and Analysis of Chatbots

An architectural overview of an intelligent chatbot, which consists of three main layers: the presentation layer, the machine learning layer, and the data layer was discussed in this study by [11]. The main methods used in the study include natural language processing (NLP), natural language understanding (NLU), and a decision engine, which work together with a knowledge base to achieve artificial intelligence (AI) using recurrent neural networks (RNNs) and long short-term memory (LSTM) networks. The data used in the study includes user interaction history and a knowledge base that represents the domain-specific source content used for training purposes. The study also discusses different chatbot platforms and development frameworks, such as Facebook Bot Engine, Dialogflow, and Microsoft Bot Framework, and their advantages and limitations. The results show that the combination of NLP, NLU, and the decision engine, along with the knowledge base, can effectively generate intelligent responses using RNN and LSTM models. However, the study also identifies several challenges in the development of intelligent chatbots, such as eliminating ambiguity in conversation, keeping track of the context of the conversation, incorporating loops, splits, and recursion in conversation, ensuring consistency in natural language interpretation, building character and persona, and providing emotional support capabilities.

A patent analytic framework that begins from patent-based ontology building, followed by patent management map and Technology Function Matrix (TFM) analysis was employed in this study by [12]. The main data source for the study was the Derwent Innovation (DI) global patent database. The study used text-mining approaches such as k-means clustering algorithm and Latent Dirichlet Allocation (LDA) topic modeling to construct a four-level hierarchical ontology structure and reduce human interference during the process. The ontology map was then utilized as the basis for sustainable and strategic R&D planning, from which researchers could quickly understand the development trends of key technologies and identify technology gaps. In addition to the patent analysis, the study also reviewed academic articles to find emerging technologies, and a systematic literature review (SLR) approach was used to ensure methodological rigor and quality. The results of the study identified several

emerging technologies, including knowledge graph as a feature generation framework, deep learning as the core of the main method, and noise reduction as the focus of recent speech recognition technology. The study also found that context is the main research subject, whether it is the exploration of the knowledge base or the logic of the algorithm. The TFM analysis revealed that the transformer model and speech-generating device are the main technologies of the current market and have a positive impact on almost all functions, while the automated control function is more widely used than others. The study acknowledged the limitations of using only patent data as the data source and the need for domain experts to be involved in the entire operation of the framework for key term extraction and result verification.

A hybrid model that integrates the transformer framework and an API for a large language model (LLM)/chatbot that exists to provide centralized access to educational materials was employed in this study by [13]. The data for the study consists of a local database of PDF files containing educational content. The study also utilizes advanced techniques such as text segmentation, contextual searches using OpenAI Embeddings, and indexing with the FAISS tool to enable efficient retrieval of relevant information. Additionally, the model incorporates a decision-making mechanism that evaluates multi-criteria factors, including semantic relevance, grammatical correctness, and previous response history, to select the optimal response. To evaluate the performance of the hybrid model, the study uses the 20 Newsgroups dataset, a well-known benchmark for multi-class text classification. The analysis of the model's performance metrics, including precision, recall, and F1 score, reveals that the hybrid model achieves a weighted average precision of 0.781, a weighted average recall of 0.745, and a weighted average F1 score of 0.760, indicating a robust and balanced performance across the various categories. The study highlights the model's ability to provide accurate and comprehensive responses to user queries, making it a valuable tool for enhancing the accessibility and organization of educational materials in modern learning environments.

A chatbot system that utilizes a knowledge database to model human-to-machine conversations was employed in this study by [14]. The core of the chatbot system is stored in a relational database management system (RDBMS), which houses the knowledge base in the form of pattern-template pairs. The knowledge base is constructed using Indonesian conversational patterns, and the RDBMS used is MySQL. The study also utilized various methods, such as the bigram model for sentence similarity measurement, the Witten-Bell smoothing algorithm for probability estimation, and stored procedures and functions in the RDBMS for pattern matching and other supporting processes. The study tested the functionality of the chatbot system through modular testing, which involved executing the stored programs with various input parameters and analyzing the outputs. The results showed that the chatbot system was able to effectively normalize user inputs, identify keywords, and retrieve appropriate responses from the knowledge base using the pattern matching process. The study also demonstrated the integration of the chatbot core with standalone applications developed in programming languages like Pascal and Java, showcasing the versatility of the system. Overall, the study presents a comprehensive approach to building a chatbot system that leverages a knowledge database and various natural language processing techniques to facilitate human-to-machine conversations.

A qualitative coding process inspired by Grounded Theory to derive a conceptual model of social characteristics for chatbots was implemented in this study by [15]. The data consisted of 56 scientific papers from various domains, including human-computer interactions, learning and education, and information and interactive systems. The researchers also used a second coder to review the produced set of characteristics and participate in discussion sessions to identify characteristics that could be merged, renamed, or removed. The study derived a total of 11 social characteristics, grouped into three main categories: conversational intelligence, social intelligence, and personification. The results provide insights into the benefits, challenges, and strategies associated with each characteristic, as well as their interrelationships. For example, the study found that proactivity can influence perceived personality and conscientiousness, while conscientiousness can manifest

emotional intelligence and personalization. The limitations of the study include the exclusion of embodied and speech-based conversational agents, as well as the potential for some studies that include social aspects of chatbots to have been missed due to the diverse definitions of chatbots across the literature.

The study reveals a significant surge in research on chatbots since 2021, primarily centered on technology adoption, ethics, and security. However, it highlights a gap in the exploration of individual factors and strategies affecting chatbot adoption and spread by [71]. Utilizing co-citation and text analysis of 386 scholarly articles from the Web of Science database alongside 4,840 news articles, the study delineates the intellectual framework and prevailing research trends. It proposes a future research agenda that emphasizes enhancing chatbot development and performance, as well as examining consumer responses and social acceptance. The study employed a variety of methods to examine chatbot research. A systematic literature review was conducted on 386 articles from the Web of Science database to identify trends and intellectual structures shown in figure 2. Co-citation analysis was utilized to understand the academic framework and characteristics by examining article citations. Text analysis was used to analyze keywords and sentiment in news articles related to chatbots, providing a comparison with academic research. Additionally, topic modeling was employed to explore extensive collections of scholarly publications, identifying research developments and emerging directions. The results mentioned that research on chatbots has been rapidly increasing since 2021, focusing on technology adoption, bias, ethics, and security. However, there is a notable lack of studies examining the individual factors and strategies that influence the adoption and spread of chatbots. To uncover the major articles and research topics and to highlight the intellectual structure of chatbot research, the study utilized co-citation analysis. Based on the identified research gaps and trends, the article proposes a future research agenda. The study acknowledges several limitations. Despite systematic literature reviews (SLRs) aiming to reduce bias, they remain susceptible to self-reporting bias and subjectivity, which can affect reproducibility. The study's heavy reliance on academic research may overlook valuable insights from gray literature such as news articles, blogs, and white papers. Additionally, constraints in data collection from the Google News feed make it

challenging to replicate the exact dataset in the future. Furthermore, the effectiveness of meta-analysis is limited by the availability of sufficient prior studies, and there is a risk of synthesizing research without adequately distinguishing the quality of the studies.

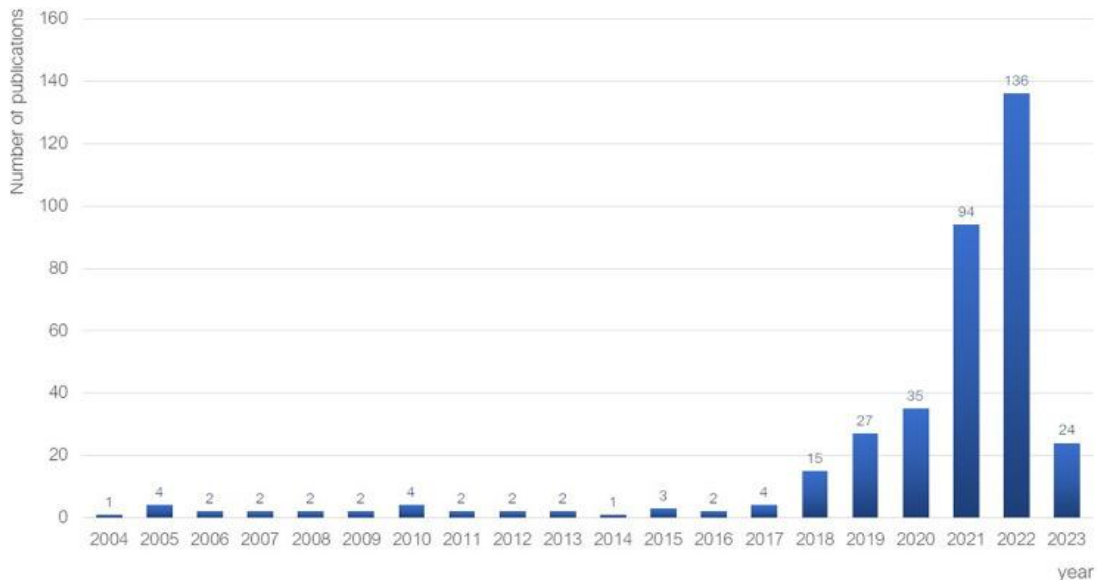


Figure 2: Distribution of the 386 Articles (2004–2023 February) [71]

The study aimed to investigate users' opinions, satisfaction, and attitudes toward anxiety and depression chatbot apps by analyzing 205,581 user reviews from the Google Play Store and Apple App Store by [72]. Reviews were categorized into positive and negative meta-themes, with topic modeling and thematic analysis employed to identify specific themes and subthemes. Positive themes included confidence and affirmation building, adequate analysis and consultation, a caring friend-like approach, and ease of use. Negative themes encompassed usability issues, update problems, privacy concerns, and lack of creative conversations. The study's methodology involved several key steps. Data collection was conducted by extracting reviews from the Apple App Store and Google Play Store using scraper tools and Python libraries. During data preprocessing, the text was normalized, irrelevant content was removed, and non-English reviews were filtered out. Reviews were then annotated by categorizing them as positive or negative based on user ratings. Data vectorization was achieved using the bag-of-words approach to convert text into numerical form. Topic modeling, specifically latent Dirichlet allocation (LDA), was applied to identify

themes within the reviews. Finally, thematic analysis was performed on the identified topics to categorize them into overarching themes and subthemes. The study revealed several key results. Positive reviews highlighted users' appreciation for confidence and affirmation building, adequate analysis and consultation, a caring friend-like approach, and ease of use. In contrast, negative reviews pointed out usability issues, update problems, privacy concerns, and noncreative conversations. Analyzing 205,581 user reviews using machine learning techniques, the study identified themes and subthemes. Thematic analysis uncovered four main themes for both positive and negative reviews, each comprising several subthemes. The article acknowledges several limitations. The study analyzed only English reviews, excluding non-English comments. Due to the Apple App Store's privacy policy, the extraction was limited to a maximum of 500 reviews per app. Reviews containing only emojis or emoticons were excluded from the analysis. Additionally, neutral and negative reviews were combined into a single category, which could be considered a limitation.

The study investigated interactions with the social chatbot SimSimi during the COVID-19 pandemic to explore individuals' informational and emotional needs by [73]. It found that users engaged in discussions about COVID-19-related questions, preventive measures, the pandemic's physical and psychological impacts, and life during the crisis, with negative sentiments being prevalent, particularly regarding masks, lockdowns, and fears. Users in the United States showed more negative sentiments compared to those in Asian countries. The study underscores the potential of chatbots to offer health information and emotional support during global health emergencies. Methodologically, the study analyzed chat data from SimSimi, covering interactions from five countries (United States, United Kingdom, Canada, Malaysia, and the Philippines) between 2020 and 2021. It employed Latent Dirichlet Allocation (LDA) to identify 18 topics, utilized the Linguistic Inquiry and Word Count (LIWC) dictionary for sentiment analysis, and filtered out explicit and harmful content using Google's Jigsaw Perspective API and an Offensive Profane Word List. The study revealed several key results. It identified 18 COVID-19-related topics, which were organized into five main themes: inquiries about COVID-19, preventive measures, the outbreak, physical and psychological impacts, and life during the pandemic. Sentiment analysis showed that users had more negative feelings when discussing masks,

lockdowns, and pandemic-related worries, while positive sentiments were more common in casual conversations. Additionally, users in the United States expressed more negativity compared to those in Asia regarding COVID-19 discussions. The findings suggest that chatbots were used for both information and emotional support during the pandemic, highlighting their potential role in public health support. The study has several limitations. It relied on data from a single chatbot, SimSimi, which may not reflect interactions with other chatbots. The analysis was confined to English conversations from five countries, potentially overlooking insights from non-English speakers and other regions. Sentiment analysis was based on the LIWC dictionary, which might not fully capture the nuances of user emotions. Additionally, while the study removed toxic conversations for privacy and ethical reasons, this could have led to the exclusion of some relevant negative sentiments.

The study explored how individuals interacted with the social chatbot SimSimi during the COVID-19 pandemic to understand their informational and emotional needs by [74]. It found that users discussed topics such as preventive measures, the COVID-19 outbreak, and its physical and psychological impacts, often expressing negative sentiments about masks, lockdowns, and case counts. Notably, users in the United States showed more negative sentiments compared to those in Asian countries. The study underscores the potential of chatbots to offer health information and emotional support during global health crises. Methodologically, Replika users (N=66) were recruited via social media platforms like Facebook and Reddit in the spring and summer of 2019. They completed a survey with open-ended questions about their Replika usage and provided basic demographic information. All procedures received approval from Lake Forest College's Human Subjects Review Committee (TA04152019) and adhered to the 1964 Declaration of Helsinki and its subsequent amendments. The study found that users contacted Replika primarily due to interest, for social support, and to manage mental and physical health conditions. They engaged in a broad range of discussions, covering topics such as intellectual subjects, life and work, recreation, mental health, interpersonal connections, Replika itself, current events, and other individuals. The study indicates that a single social chatbot can offer diverse forms of support and emphasizes that user interest plays a crucial role in motivating chatbot usage. The study has several limitations. The use of surveys

may introduce self-selection bias, limiting the ability to generalize findings to a broader population. Additionally, the research only addresses why users initially contacted Replika and does not explore reasons for continued interaction. It also cannot determine if discussion topics remained consistent over time or if some topics became more prevalent later. Furthermore, the findings are based on a relatively small sample size, which may impact the external validity of the results.

The study introduces a decision-making framework for choosing the best customer service chatbot in the telecommunication industry by combining Analytic Hierarchy Process (AHP) and Combined Compromise Solution (CoCoSo) methods by [75], utilizing single-valued neutrosophic sets (SVNSs) to manage uncertainty, and demonstrates its effectiveness through a case study in Egypt, with sensitivity analysis to confirm the model's robustness. The proposed method is given in the figure 3. The study's results reveal that the Analytic Hierarchy Process (AHP) was employed to assign weights to nine criteria for selecting a chatbot, with the ninth criterion being the most significant and the first the least. Using the Combined Compromise Solution (CoCoSo) method, eight chatbots were ranked, with the second chatbot emerging as the top choice, followed in order by the seventh, third, fifth, first, eighth, sixth, and fourth. The consistency ratio of the experts' evaluations was 0.079, demonstrating reliable and consistent data. The study notes several limitations, including the inability of traditional methods to address indeterminacy and uncertainty in decision-making, which can impact result accuracy. It also mentions that prior research often involved small sample sizes, potentially limiting the depth of insights. Additionally, relying solely on one method for calculations may not fully capture the complexity of the decision-making process. Furthermore, the study points out that not considering both subjective and objective factors can lead to incomplete evaluations.

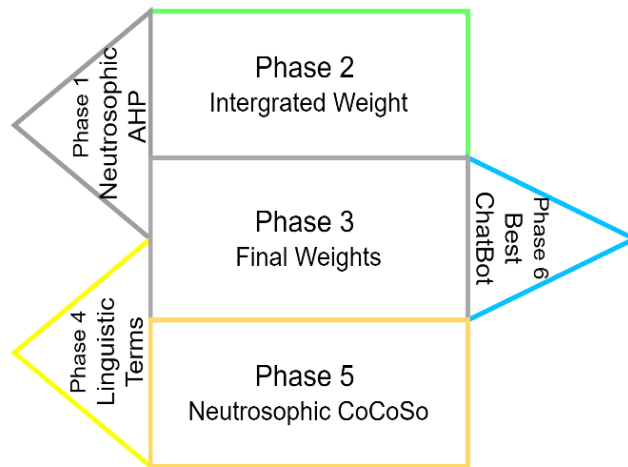


Figure 3: Proposed Framework [75]

The study focuses on creating a VR empathy-centric counseling chatbot system (VRECC) designed to assist college students dealing with stress from academic pressures, personal relationships, health concerns, and career uncertainties by [76]. The system integrates virtual reality technology with psychological principles to deliver empathetic responses through multi-turn conversations, utilizing BERT models for accurately classifying sentiments and issues. To evaluate its effectiveness, the study employed a questionnaire to assess students' stress levels, psychological sensitivity, and life impacts. The VRECC was developed with BERT models to facilitate empathetic dialogue and featured an avatar-based chatroom built with the Photon engine, which supports real-time interactions in a virtual setting. System verification involved participants using the VR chatbot, with their responses compared before and after using the system to determine its impact. The study found that the VR empathy-centric counseling chatbot (VRECC) effectively lowered stress levels among participants and led to a significant reduction in psychological sensitivity. However, there was no notable improvement in life-impact scores, which include behavioral and physical effects. Overall, the study suggests a promising future for combining VR, AI-driven sentiment analysis, and counseling chatbots to enhance students' psychological well-being and quality of life. The figure 4 shows the architecture and process of Chabot modules. The study acknowledges several limitations, including a small sample size of only 34 participants, which may not reflect the broader student population. It also focused on short-term effects without evaluating the long-term impacts on stress and psychological sensitivity. Additionally, the research was limited to a university setting, potentially restricting the generalizability of the findings to other

contexts. Lastly, the effectiveness of the VR empathy-centric counseling chatbot could be affected by the quality and accessibility of the VR technology used.

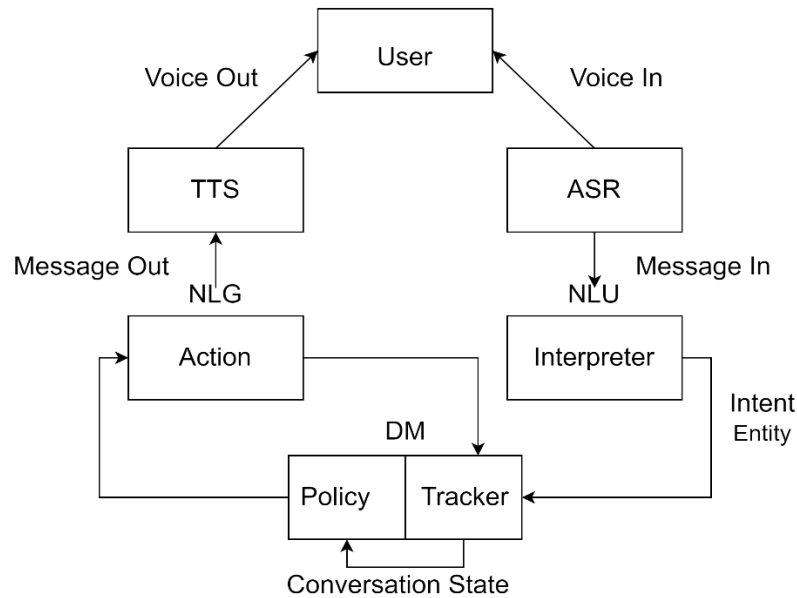


Figure 4: Architecture and process of chatbot modules [76]

The study aimed to evaluate the effectiveness and safety of chatbots for enhancing mental health by summarizing and aggregating findings from prior research by [77]. It utilized a systematic review approach, adhering to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines. Researchers conducted searches across seven bibliographic databases, Google Scholar, and examined reference lists from included studies and relevant reviews. Two independent reviewers selected the studies, extracted data, and assessed bias risk. The data were then synthesized through both narrative and statistical methods, with statistical analyses carried out using Review Manager (RevMan 5.3). The study revealed that chatbots significantly reduced depression severity, though the clinical significance of this improvement remains uncertain. For anxiety, results were inconsistent, with some studies reporting benefits while others found no significant effects. There was no notable enhancement in subjective psychological well-being. Overall, chatbots were deemed safe, with no adverse events or harms reported. Figure 5 shows the flow chart of study selection process. The study's limitations include insufficient evidence to definitively determine the effectiveness and safety of chatbots, due to the lack of clinically significant effects and conflicting results. Many of the included studies had a high risk of bias, which impacts the reliability of the findings. Additionally, the limited number of studies for each outcome made it challenging to reach robust conclusions.

Conflicting results were also observed for certain outcomes, such as anxiety severity and positive and negative affect.

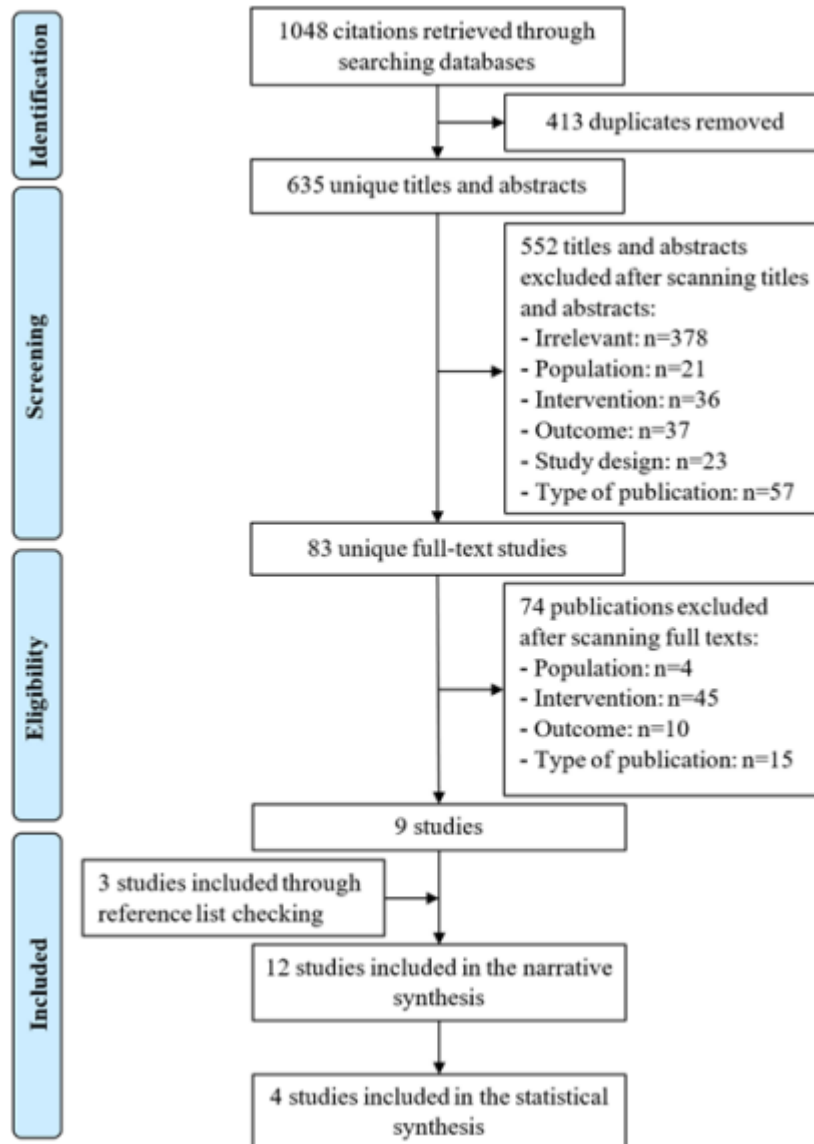


Figure 5: Shows the study selection process [77]

The study analyzed log data from the ChatPal chatbot to understand user behavior by examining usage patterns, identifying user archetypes through k-means clustering, and exploring feature associations using association rule mining by [78]. It considered various user characteristics, including tenure, mood logs, and interaction frequency. K-means clustering revealed three user types abandoning users, sporadic users, and frequent transient users while association rule mining identified popular conversation topics, such as “Treat yourself like a friend.” The research received ethical approval from multiple ethics committees across different universities and

countries. Insights from the study aim to enhance the app by focusing on frequently accessed features and understanding user behaviors. The study on the ChatPal mental well-being chatbot revealed that out of 579 adult users, interactions were highest around breakfast, lunch, and early evening. It identified three user types: "abandoning users" (81.7%), "sporadic users" (16.1%), and "frequent transient users" (2.2%). The most accessed conversation was "Treat yourself like a friend," though only 11.7% of users revisited it. Additionally, strong associations were observed between the "Treat yourself like a friend," "soothing touch," and "thoughts diary" conversations. The study faced several limitations, including challenges in tracking session lengths due to the absence of an "end of session" variable, potential bias from the app's rigid menu structure influencing user interactions, and limited analysis of mood logs since mood data were only collected at the beginning of each session. Additionally, discrepancies arose from recording log data based on server time rather than local time, leading to inaccuracies for users in different time zones.

3.4 Chatbots for Student Support and Engagement

A systematic literature review focusing on the use of Chatbots in education was discussed in the study by [16]. This approach followed established guidelines for systematic reviews in software engineering, including planning, conducting, and reporting phases. The review aimed to answer four main questions about how Chatbots are being used in educational settings. A thorough search process was used, covering several digital databases with a well-crafted search syntax combining keywords related to Chatbots and education. Both manual and automated searches were employed to ensure all relevant articles were found. The results of the study provided a detailed look at how Chatbot technology is being integrated into education. Chatbots are used in various areas such as teaching, learning, administration, assessment, advising, and research and development. They primarily function as conversational agents, offering personalized information and quick responses, which help to enhance student engagement and support. The study highlighted several benefits of using Chatbots in education. These include seamless content integration, fast access to information, increased motivation and engagement among students, the ability to handle multiple users at once, and providing immediate assistance. The study also pointed out several challenges in implementing Chatbot systems in educational settings. These challenges include ethical concerns, the lack of proper evaluation methods, issues with user attitudes, complexities in programming, and difficulties in

integrating data. These challenges suggest that more research is needed to improve the use of Chatbot technology in education and to address these issues.

Using a mixed-method research approach to explore how effective, efficient, and satisfying chatbots are in education, especially as assistant tutors, while also identifying their limitations was discussed in the study by [17]. This included gathering both quantitative and qualitative data. Methods involved an Evidence-Based Practice approach, which was adapted from models used in clinical decision-making, a systematic review of literature following PRISMA guidelines, and an analysis of interactions between chatbots and students. Data collection included a pilot exercise where students communicated with a chatbot, providing insights into their perceptions and expectations. Additionally, the study examined how teachers view and use chatbots through a systematic review approach. The findings showed that chatbots play a supportive role in teaching and learning. They help students by giving immediate, personalized answers to common questions, supporting reflective thinking and metacognition, and boosting motivation to learn. However, the study also identified several limitations. One key issue is that the effectiveness of chatbots depends heavily on the quality of the input data. There is also a need for human oversight to ensure the information provided by the chatbot is accurate and unbiased.

The study used a Systematic Literature Review method, guided by the PRISMA framework, to examine Intelligent Tutoring Systems in different educational fields was discussed in the study by [18]. Researchers looked for relevant publications in databases like Scopus, Web of Science, and Google Scholar, focusing on articles published from 2016 to 2022. They used inclusion and exclusion criteria based on PICO (Population, Intervention, Comparison, Outcome) questions and SLR tools, which helped them refine their search and selection process. The results showed that ITS are used in various educational disciplines, with the most common field being Computer Sciences. Artificial intelligence approaches are frequently used in ITS, including adaptive guidance, learner assessment, and categorization. The study found that ITS have a significant impact on student achievement, especially in schools and universities. The study did have some limitations. It relied on publications from selected databases, which might not cover all the existing literature on the topic. This could lead to an incomplete picture of the ITS landscape.

Exploring chatbot technology using various methods, including historical analysis, clarifying technological concepts, and classifying chatbots based on

knowledge domain, services provided, and goals was discussed in the study by [19]. It delves into the design and development of chatbots, employing techniques like pattern matching, AIML (Artificial Intelligence Markup Language), LSA (Latent Semantic Analysis), and NLU (Natural Language Understanding) to generate human-like responses. The findings reveal a rapid increase in interest in chatbots since 2016. Advances in AI and machine learning have significantly improved chatbot capabilities, enhancing their effectiveness in customer service, emotional interactions, and natural conversations. The study also highlights how social stereotypes influence chatbot design and the potential for chatbots to serve as both tools and companions. A significant limitation is that chatbots currently lack the ability to truly understand empathy.

Looking at how chatbots are used in education, focusing on their roles as tutors, student evaluators, and conversational partners was discussed in the study by [20]. It reviewed various ways chatbots are applied, such as personalized learning through Technology Mediated Learning (TML), Spaced Interval Learning to reinforce memory, and assessing composition skills using unsupervised machine learning. The study also explored how chatbots can reduce the workload of tutors by automating responses to common questions and assessments. Additionally, it examined the integration of chatbots into classroom environments and social platforms. The results showed that chatbots can greatly enhance student interaction and engagement. They can adapt to individual learning speeds, support social learning, and help teachers identify student weaknesses through conversation logs. Chatbots were also found to be effective in providing immediate feedback and facilitating group work and projects. One major limitation is that chatbots are not empathetic and sometimes provide incorrect information. This highlights the importance of having human oversight to ensure accuracy and maintain the quality of interactions. The study concluded that while chatbots have great potential to enhance education, they are not a replacement for human teachers. Instead, they should be seen as complementary tools that require ongoing development and evaluation. Chatbots can support teachers by handling routine tasks and providing personalized learning experiences for students, but the human element in education remains irreplaceable. The study underscores the promise of chatbots in education, pointing out their ability to make learning more interactive and engaging. However, it also stresses the importance of addressing the current limitations and continuously improving chatbot technology to maximize its benefits in educational settings. By doing so, chatbots can become more effective

partners in the learning process, providing valuable support to both students and educators.

Using a pedagogical framework called CHAT-ACTS, which incorporates customized chatbots into dynamic and self-directed learning to boost student engagement and learning outcomes was discussed in the study by [21]. It employed strategic actions like Evaluation, Feedback, and Planning in the Personalized Chatbot mode, while focusing on Study Tactics and Goal Setting in the Self-Regulated Learning mode. Additionally, it highlighted Active-Based Learning and Teaching Strategies in the Active Learning mode. The results showed that the CHAT-ACTS framework helped create strong connections between these learning modes. This integration allowed for effective feedback, goal setting, and the use of active learning techniques, which together could enhance student motivation, engagement, and achievement in educational settings. However, the study identified a few limitations. One major issue is that chatbots are not empathetic and can sometimes provide incorrect information. This lack of emotional understanding can impact the quality of student interactions. Another limitation noted was the absence of empirical evidence directly linking Active Learning and Self-Regulated Learning. This suggests a need for further research to validate the effectiveness of the CHAT-ACTS framework in different educational contexts.

Using a multi-phase approach to examine research publications on Artificial Intelligence in Education (AIEd) was discussed in the study by [22]. It combined bibliometrics, analysis of categorical meta-trends and inductive content analysis to get a comprehensive view. Researchers began by searching the Web of Science database and AIEd-specific journals, applying strict criteria to find empirical, evidence-based studies. They analyzed the data using quantitative bibliometrics to measure research output, a categorical meta-trends analysis to track trends over time, and inductive content analysis to assess the content qualitatively. The results showed a diverse landscape of AIEd research, with 40 empirical studies from 16 countries, mainly the USA and China. These studies covered various educational settings and subjects. They demonstrated that AI technologies, including chatbots, expert systems, intelligent tutors, machine learning, and personalized learning environments, and visualizations, can enhance educational outcomes. The study noted some limitations. One major issue is the potential for selection bias because the focus was on specific databases and journals. This means that some newer journals not indexed in the Web of Science were excluded, possibly leading to an incomplete picture of current AIEd research. The

study also emphasized the need for more empirical research on AI technologies in real educational settings. This is important to bridge the gap between the potential of these technologies and their practical implementation in classrooms. The study highlights the wide range of research in AIEd and the positive impact of AI technologies on education. It points out the need for more comprehensive and inclusive research to get a complete understanding of the field. By addressing these limitations and focusing on real-world applications, future research can better align technological advancements with practical educational needs.

A thorough literature review to gather essential information about chatbots, covering their history, categorization, implementation technologies, and applications was discussed in the study by [23]. The researchers improved existing chatbot classification systems by adding a 'Permissions' category and expanding the 'Communication channel' category to include image input. They also proposed a general architectural design for chatbots and highlighted critical considerations before system design. The study discussed the evolution of chatbots, noting their growth from simple pattern-matching programs to complex systems capable of engaging in natural dialogues, handling various tasks, and even showing emotional intelligence. Advances in machine learning and sentiment analysis have enabled chatbots to respond emotionally to customers, making them more effective. It was found that undisclosed chatbots could be more productive than inexperienced sales staff. The study identified several limitations of current chatbots. One issue is potential bias in gender representation among chatbots, which can reinforce stereotypes. Another challenge is creating chatbots that are truly empathetic and contextually aware, which is crucial for more meaningful interactions. To address these issues, the study suggested various mitigation strategies. Despite these challenges, the researchers concluded that chatbots have made significant progress and hold great potential for the future. They emphasized the need for chatbots to become smarter and better at human communication, especially through speech. This improvement would make chatbots more useful in various fields, from customer service to education. The study shows the significant advancements in chatbot technology and its potential benefits. It also stresses the importance of addressing current limitations, such as bias and lack of empathy, to improve chatbot effectiveness. By focusing on these areas, future research and development can help create chatbots that are more intelligent and capable of engaging in more natural and meaningful conversations.

Reviewing existing chatbot technologies, focusing on their ability to generate appropriate responses was discussed in the study by [24]. It traces the historical development of chatbots from the early "imitation game" to modern AI and NLP advancements. Chatbots are categorized into task-oriented and non-task-oriented systems. The study explores various approaches within these categories, such as supervised and unsupervised methods for task-oriented chatbots, and retrieval-based and generation-based models for non-task-oriented chatbots. The results show a significant evolution in chatbot capabilities, with current models able to engage in more natural and contextually relevant dialogues. Despite these advancements, several challenges remain. Chatbots still need better contextual understanding, improved emotional and sentiment analysis, and enhanced user interface design. One major limitation is that chatbots are not empathetic and can struggle to understand and respond to human emotions. This lack of emotional intelligence can affect the quality of interactions, making them seem less human. The study concludes that while chatbot technology has come a long way, there is still much work to be done. Enhancing AI integration to improve conversational abilities and developing a standardized quality assessment framework are crucial steps for advancing the field of human-computer interaction. Addressing these limitations will help create chatbots that are smarter, more empathetic, and better at engaging in natural conversations. Also, the study shows the progress in chatbot technology and its potential benefits. However, it also emphasizes the importance of tackling existing challenges, like improving empathy and emotional understanding, to make chatbots more effective and human-like in their interactions.

A comprehensive approach to look at how chatbots can be used in educational settings was discussed in the study by [25]. It focused on how Artificial Intelligence (AI), machine learning, and deep learning techniques can enhance chatbot abilities for interactive communication and learning support. The study also examined the impact of chatbots on core educational tasks like teaching and knowledge transfer, especially for administrative and repetitive tasks that could be automated. From an organizational perspective, the study considered how educational institutions could use chatbots for providing information, support services, and integrating with digital platforms like eLearning. The results showed that chatbots could significantly help both learners and tutors by offering accessible educational content, procedural advice, and personalized tutoring. This can make the learning environment more efficient. Chatbots also have the potential to support students with special needs and boost student engagement through dynamic, real-time interactions. The study found several benefits, but it also

pointed out some limitations. One concern is the safety and privacy of student data collected by educational chatbots. There is also the potential for chatbots to disrupt the traditional teacher-student dynamic, which needs careful consideration.

Exploring how chatbots are being integrated into the education system, using a socio-constructivist approach to understand their role as virtual assistants and tutors was discussed in the study by [26]. It examines different aspects such as how chatbots communicate, their programming methods, and machine learning techniques. The research also investigates how chatbots impact educational stakeholders in the United States, assessing their potential to improve institutional competitiveness. The findings show that many believe AI can significantly transform education, and numerous institutions are experimenting with AI as part of their strategies. Chatbots have proven effective in handling routine tasks, providing practice in virtual languages, and supporting students with programmed learning materials. However, the study recognizes some limitations. For example, chatbot development in education is still in its early stages, and there are challenges in creating machine learning-based chatbots that can effectively respond to a wide range of questions. Another limitation is that chatbots lack empathy and emotional responsiveness. They may struggle to understand and appropriately respond to the emotions of students, which is important for creating a supportive learning environment. This aspect of emotional interaction remains a challenge for chatbot technology in education.

A systematically reviewing how chatbots are evaluated, focusing on research published between 2016 and 2020 was discussed in the study by [27]. It aimed to identify methods used to assess chatbots, categorizing them based on usability concepts: Effectiveness, Efficiency, and Satisfaction as per ISO 9214 guidelines. Initially, the researchers analyzed 204 publications related to chatbots, applying criteria like language and availability online. This narrowed down the field to 53 papers, which were categorized and synthesized for their findings. The study highlighted a preference for evaluating chatbots based on Efficiency, closely followed by Satisfaction. Over the years, there were noticeable shifts in the distribution of these evaluation methods, with Efficiency-based approaches showing a consistent increase. Most papers focused on a single evaluation method, especially when assessing Effectiveness. When two methods were used, Efficiency and Satisfaction were commonly paired together. The study acknowledged its limitations. It only included papers that met specific criteria, potentially missing out on relevant studies that didn't fit these parameters or weren't freely accessible online. Moreover, the absence of a universally accepted standard for

evaluating chatbots may have contributed to the diversity of methods observed in the reviewed literature.

The study by [28] covered the evaluation of the LearningBot, an android-based chatbot intended to facilitate learning in Object-Oriented Programming (OOP), with a focus on undergraduate computer science students as participants. The methodology involved developing a knowledge base for the chatbot, creating a user-friendly graphical interface, and establishing a robust system architecture. To assess usability, researchers used the System Usability Scale (SUS). They also measured the impact on students' learning by evaluating cognitive load and learning outcomes. The findings revealed that compared to traditional search engines, the LearningBot notably reduced both the intrinsic (internal mental effort) and extraneous (external, unnecessary effort) cognitive loads. Moreover, students using the LearningBot achieved higher scores in post-tests assessing OOP tasks, indicating improved learning outcomes. The study has limitations. It primarily focuses on OOP and hasn't explored how the LearningBot might integrate into broader educational contexts or other subject domains. This scope limitation suggests that while effective within its specific domain, further research is needed to understand its potential in diverse educational settings.

A mixed-method approach to examine chatbot applications in university education, starting with a qualitative analysis followed by quantitative exploration during the COVID-19 pandemic was discussed in the study by [29]. It followed the PRISMA statement for systematic literature review, gathering manuscripts from databases like Scopus, ERIC, and IEEE Xplore, and applying specific criteria to select relevant studies. The findings highlighted that chatbots positively impacted student interaction and academic performance. Many studies reported increased student engagement and satisfaction due to chatbot use. However, the study acknowledged its limitations. It focused on a specific timeframe (the COVID-19 pandemic), which may restrict the generalizability of the findings beyond that period. Additionally, there is a possibility of bias in the selection of manuscripts, which might not fully represent all aspects of chatbot usage in education.

Developing an automated chatbot for the education system using various advanced technologies like machine learning, natural language processing (NLP), pattern matching, and data processing algorithms was discussed in the study by [30]. It began with a comprehensive survey of existing applications across fields such as medical care, marketing, and education. Specific examples included psychiatric counseling chatbots for mental health support and educational chatbots designed for visually impaired individuals. Key components of the chatbot system included input

adapters to receive user queries, logic adapters to process these queries and generate responses, and output adapters to deliver these responses effectively. The training system was crucial, involving the creation of a knowledge graph based on example dialogues to enhance the chatbot's learning abilities. The study's findings showcased the chatbot's ability to autonomously respond to student inquiries by identifying keywords and generating replies from either a static database or online sources. This approach ensured a scalable and secure response mechanism for handling diverse educational queries. The study identified a limitation in the chatbot's design. It lacks empathy and emotional understanding, which can be crucial in educational contexts where students may require personalized emotional support. This limitation underscores the challenge of creating chatbots that can effectively engage with users on an emotional level.

A systematic review of recent literature to explore technologies integrated into chatbot architectures for educational institutions was discussed in the study by [31]. Articles published within the last five years from databases like IEEE Xplore and Google Scholar were reviewed, resulting in 22 relevant articles after applying specific selection criteria. The findings emphasized common technological choices in chatbot development. Most chatbots utilized a web platform for their user interface, Dialogflow for managing dialogues, and Firebase as the database backend. These technologies were favored for their capability to streamline user interaction and efficiently manage data. A limitation of the study is its focus on articles from specific databases and within a defined timeframe. This approach may overlook emerging technologies or alternative approaches used in chatbot architectures outside of the selected sources. Future research could broaden its scope to encompass a wider range of databases and consider older literature to provide a more comprehensive overview of technological trends in educational chatbot development.

Developing a chatbot system using AI and NLP techniques to create a user-friendly interface for college inquiries was discussed in the study by [32]. They implemented preprocessing to identify context, allowing the system to handle personalized queries after user authentication. For general conversations, they utilized an AIML response system. Additionally, a query analysis and response system were employed to deliver information across various college domains, using semantic sentence similarity algorithms to match user questions with predefined queries. The results demonstrated that the chatbot effectively provided quick, accurate, and informative responses. This improved user experience on college websites by addressing inquiries related to exams, admissions, academics, attendance, GPA

calculations, placement services, and other related activities. A limitation of the study is the chatbot's lack of emotional intelligence. It doesn't understand or respond empathetically to users' emotional needs, which could limit its effectiveness in situations where students seek support or guidance beyond factual information.

A systematic literature review approach to explore the impact of AI chatbots in education was discussed in the study by [33]. It began with a thorough search across multiple academic databases, employing a structured search string designed to capture relevant studies. Following this initial phase, the researchers applied predefined criteria to screen and select articles that met their inclusion criteria. This collaborative effort ensured consistency in the selection process, involving stages of reviewing metadata, assessing study quality, and analyzing full texts, ultimately identifying 67 studies deemed pertinent to their investigation. The findings of the study underscored several significant benefits of AI chatbots in educational contexts. Both students and educators reported positive outcomes, highlighting improvements in learning achievements, personalized learning experiences tailored to individual needs, and valuable time savings for educators who could focus more on instructional tasks. These benefits suggest that AI chatbots have the potential to enhance educational practices by providing efficient and customized support. The study also recognized certain limitations that warrant consideration. Ethical concerns regarding data privacy and security emerged as significant considerations in educational settings, raising questions about how personal information is handled and protected within chatbot interactions.

A comprehensive approach to explore how AI chatbots are integrated into education, focusing on various design methods such as rule-based systems and machine learning was discussed in the study by [34]. These methods, coupled with technologies like natural language processing (NLP) and machine learning (ML), enable chatbots to simulate human-like conversations effectively. The research also categorized chatbots based on their functionality, knowledge domain, services offered, goals, and how they generate responses to user inputs, underscoring the importance of making chatbots accessible via mobile devices for today's students. The findings from the study highlighted several benefits of using AI chatbots in educational settings. They contribute significantly by providing administrative support, facilitating learning through personalized interactions, and assisting students with timely access to information and resources. This enhances the overall educational experience, making learning more interactive and accessible. The study also identified a limitation worth

noting. While AI chatbots offer substantial advantages, they still face challenges in achieving true empathy and emotional intelligence. These qualities are essential in educational contexts where students may seek emotional support or nuanced understanding beyond factual information.

A systematic approach to develop a rule-based chatbot tailored for student inquiries at Asia Pacific University (APU) was discussed in the study by [35]. Following the Waterfall model, known for its structured and step-by-step methodology, the research ensured a clear path from requirements gathering to implementation, with defined deliverables at each stage. The methodology included conducting interviews with senior administrative members at APU to understand their processes and semi-structured questionnaires to gather student feedback, crucial for refining the chatbot's functionalities. Results from the study demonstrated that the "APU Admin Bot" effectively met user needs and project goals. It provided a user-friendly interface through Facebook Messenger, allowing students to conveniently resolve their queries anytime and anywhere. The chatbot streamlined administrative tasks, enhancing accessibility and responsiveness for student inquiries. The study identified limitations that deserve consideration. Firstly, the chatbot lacked backend access for administrators to update information. Also, the study's adherence to the Waterfall model posed another limitation. While this approach provided a structured framework for development, its linear nature could restrict flexibility, particularly in responding to evolving user needs or incorporating feedback iteratively throughout the project lifecycle. This rigidity may have implications for adapting to unforeseen challenges or making swift adjustments based on ongoing user interactions and feedback.

A web application-based chatbot system designed to streamline interactions between users and machines using the Naive Bayes' algorithm and Natural Language Processing was discussed in the study by [36]. The development utilized the Django framework and Chatterbot library, integrating a pre-trained database to analyze queries and generate responses effectively. This approach aimed to enhance user experience by providing prompt and accurate information related to college activities. Results from the study illustrated the chatbot's capability to deliver relevant information on various college-related inquiries, showcasing its potential to alleviate administrative burdens and offer round-the-clock support to students and parents. By leveraging NLP and machine learning techniques, the chatbot demonstrated proficiency in understanding and responding to user queries, thereby enhancing accessibility and efficiency in accessing institutional information. The study identified several limitations

that warrant consideration. Firstly, the chatbot's responsiveness was constrained by its inability to interpret emotional cues or provide empathetic responses. This limitation may impact user satisfaction, particularly in scenarios requiring nuanced or emotionally sensitive interactions where human empathy is essential.

Employing various methods to develop and evaluate college enquiry chatbots, leveraging natural language processing (NLP), machine learning algorithms, sentiment analysis, and integration with college information systems was discussed in the study by [37]. Techniques such as pattern matching, data mining, text mining, and word vectorization were applied to enhance the chatbot's ability to understand and respond accurately to user queries. Advanced tools like Rasa NLP, Dialogflow, and the Chatterbot algorithm were utilized to create sophisticated chatbot systems capable of simulating human-like conversations and problem-solving. Results from the study highlighted the effectiveness of these chatbots in managing large volumes of inquiries, offering round-the-clock support, and seamlessly integrating with college websites to enhance the overall user experience while reducing the workload on college staff. By deploying NLP and machine learning, the chatbots demonstrated proficiency in interpreting diverse user queries and providing relevant information promptly. The study identified limitations that should be considered. The chatbots were not emotionally responsive, lacking the capability to understand or respond empathetically to users' emotional cues. This limitation may affect user satisfaction, especially in situations requiring sensitivity or emotional support, where human interaction is often preferred.

A systematic literature review to investigate the application of chatbots in education was conducted in the study by [63]. The study's data set includes 2,678 publications that were initially identified and then filtered down to 74 relevant publications. To categorize research themes and conclusions, the study used a three-stage clustering technique, while systematic reviews and meta-analyses were reported using the PRISMA framework. The results revealed that chatbots in education are primarily implemented with objectives such as skill improvement (32%), efficiency of education (25%), students' motivation (13%), and availability of education (11%). The study identified four main pedagogical roles for chatbots: learning (49%), assisting (20%), mentoring (15%), and undefined (16%). The study also identified three major research challenges: aligning chatbot evaluations with implementation objectives, investigating chatbots' potential for student mentoring, and utilizing chatbot adaptive skills. The limitations of the study include the diversity of chatbot applications and designs, which makes it difficult to generalize findings across different educational contexts.

A systematic literature review method to analyze relevant papers published in SSCI journals by searching the Web of Science (WoS) database was done in the study by [66]. The study's data set contained 551 publications found using keywords such as "chatbot*" or "Conversational Agent*," which were then filtered to 482 academic papers and then limited down to 29 articles after manual screening. Other quantitative analysis techniques employed in the study included ANOVA, ANCOVA, descriptive statistics, t-tests, and correlation analysis. The results showed that the United States, Taiwan, and Hong Kong were the top contributing regions, with the highest proportion of research using guided learning methodologies. The study discovered that 20 of 29 studies (69%) utilized quantitative methods, 3 (10%) used mixed methods, and 2 (7%) used qualitative methods. The most frequently adopted analysis method was ANCOVA/MANCOVA (17%), followed by ANOVA (14%) and interviews (14%). The study found that chatbots in education are still in their early stages, with little empirical studies looking into successful learning designs or tactics (Figure 6). The main limitation of the study is the lack of empirical research on the use of chatbots in education, indicating a need for more comprehensive and innovative research to improve learning processes and outcomes.

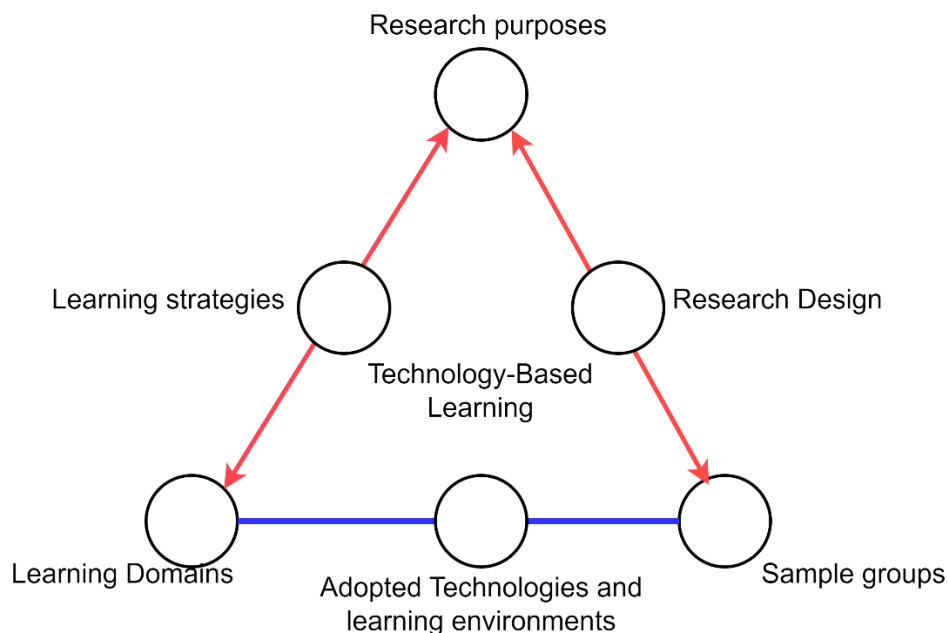


Figure 6: Coding scheme for technology-based model [64]

A systematic literature review to investigate educational chatbots, selecting 80 studies from 485 sources via the PRISMA framework, focusing on technology types

and learning outcomes was conducted in the study by [65]. The study examined how various chatbot kinds of effect student learning and educational services, comparing how these technologies aid in learning to human tutors. Data included chatbot jobs, technology used, and evaluation approaches, such as NLP algorithms and quality factors. The results revealed the variety of educational chatbots, confirming their efficiency in supporting teachers and improving learning processes, with numerous evaluation criteria used to assess their quality. The study emphasized the importance of chatbots in education and suggested further research possibilities. Notably, when compared to other machine learning models, the LSTM model performed the best, according to a review of 80 experiments. A major disadvantage noted was a lack of consistency in chatbot design features between studies, emphasizing the need for standardized creation processes and a greater focus on the contexts in which these teaching tool's function.

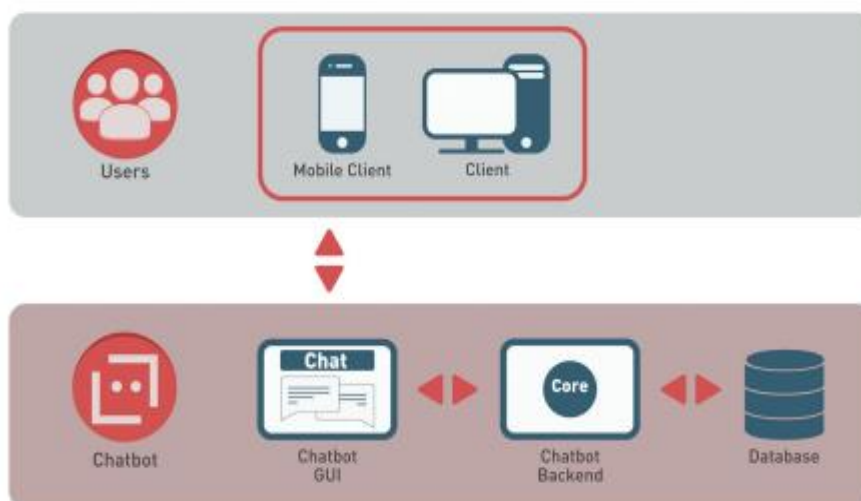


Figure 7: Chat bot architecture [65]

Two preliminary applications for chatbots within education: an FAQ chatbot and a short response quiz chatbot were developed in the study by [68]. The earliest strategies included deploying an interactive system to react to frequently requested student enquiries as well as facilitating online short answer questions. The data used included frequently requested questions about assessment, exam prerequisites, and class hours for the FAQ chatbot (Figure 5, and the short response questions students might encounter were utilized for the quiz chatbot. The study implemented Natural Language Processing (NLP) and machine learning techniques to develop these chatbots. The study's findings showed that the FAQ chatbot could anticipate and respond to common student queries, allowing educators to implement an interactive

method. It addressed and responded to typical questions well, with an 85% success rate. Meanwhile, the brief response quiz chatbot enabled the immediate, personalized identification of student misconceptions and gained significant user appreciation, with a 90% student satisfaction score. Although the study encountered technical limitations around the chatbots' understanding and the need for human interpretation, the current version demonstrated substantial promise in automating responses to general student questions, potentially reducing the workload of educators and providing immediate, individualized feedback to students.

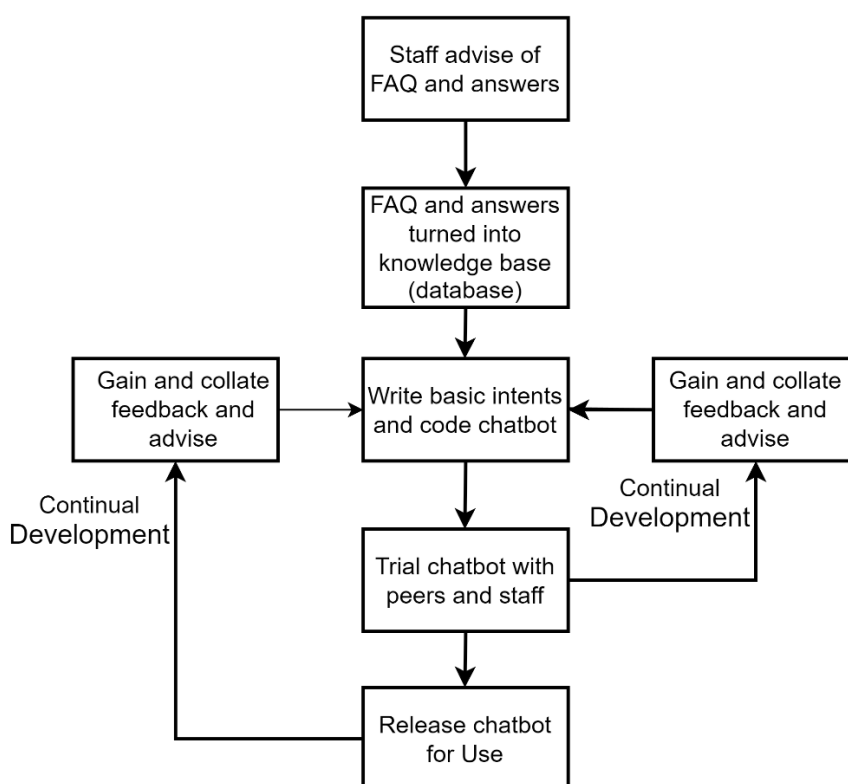


Figure 8: Flowchart of the FAQ chatbot [66]

A qualitative research approach to gain a better understanding of the ethical issues associated with the use of chatbots and AI systems in education and research was done in the study by [67]. It investigated chatbots' innovative position as machine research assistants, which supplemented the roles of human research assistants. The study claims that chatbots have the potential to revolutionize the reality of academic research, citing their efficiency in data collection, 24/7 availability, and ability to provide personalized services. It also offered creative assessment approaches to discourage the usage of AI systems while yet offering crucial opportunities for students to demonstrate their abilities. The study emphasized the importance of raising awareness

among educational actors regarding the possible misuse of chatbots, as well as implementing long-term solutions to address issues. Notably, it stated that chatbots and AI in education should be viewed as opportunities for growth rather than threats. While the findings did not include numerical numbers or machine learning models, the study's qualitative method gave a thorough grasp of the subject. However, it also acknowledged the need for future longitudinal qualitative and quantitative research to better explore the ethical and transformative aspects of chatbots in education and research.

Social Network Analysis (SNA) was used to conduct a cross-sectional analysis of tweets related to the use of ChatGPT in education, focusing on 2330 tweets from 1530 Twitter users gathered using a specific search string from December 23, 2022, to January 6, 2023 in the study by [68]. The tweet data was subsequently evaluated using sentiment analysis and t-SNE analysis. Furthermore, content analysis of interviews with 19 respondents who have used ChatGPT in education was carried out to study their perceptions and concerns. To assure trustworthiness, respondents, including educators, developers, and students, were carefully chosen, and their knowledge of chatbots was assessed on a scale of 1 to 5, with an average score of 3.02. Two coders coded the interview results using the proposed coding method. The study provided useful insights into the ongoing debate over the use of chatbots in education, as well as theories to consider when designing chatbots, emphasizing the consequences for upskilling competencies and the need to develop curricula to address advances in chatbot technology. The study also discussed the implications for establishing responsible chatbots in education and acknowledged its shortcomings, such as the small number of participants and the dependence on qualitative analysis instead of quantitative analysis. The findings and insights lay the groundwork for future research on implementing and investigating the role of ChatGPT in education, addressing the changes and outcomes brought to the education field, and delving deeper into the concerns and challenges associated with using chatbots, specifically ChatGPT, in educational settings.

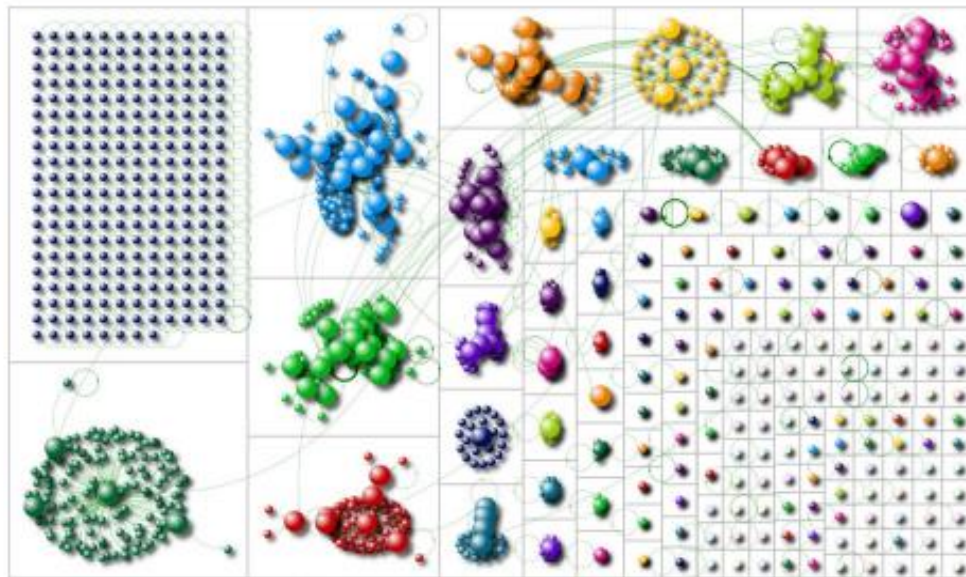


Figure 9: Chat-GPT network's bird view [68]

A study was conducted by the Warwick Manufacturing Group at the University of Warwick focused on developing and evaluating chatbot prototypes for educational settings [69]. The primary strategies included assessing and evaluating chatbot prototypes based on potential benefits discovered in the literature and prior work experiences. The study included simulated bots to determine whether important benefits such as alerting students when they get stuck and distinguishing between selling points were adequately met in the current prototype or could be addressed in the future. The study also highlighted technical obstacles for chatbot creators, such as the requirement for AI knowledge and user-friendly interfaces to efficiently update responses. While some benefits, such as deflecting tough enquiries, could be achieved utilizing systems such as IBM Watson, the difficulty of making chatbots indistinguishable from human interaction persisted. The study did not specify numerical metrics, but it did suggest that AI chatbots could improve student engagement and assistance. Among the machine learning models studied it was inferred that IBM Watson's improvements showed promise. Nevertheless, a notable limitation of the study was the ongoing need to address unanswered questions and the difficulty in predicting all scenarios for interaction within chatbot development.

Google DialogFlow technology and Heroku platform with PostgreSQL database were used to create chatbots for educational support, with specific focus on KEMTbot and an Amazon Alexa skill in the study by [70]. Intents and entities were created specifically for chatbot interaction (Figure 5), with 13 intents such as welcome, search, thanks, fields_of_study, and jokes. The chatbot's performance was examined, and 64 sessions were completed, with an average of 3.97 enquiries per session. According to a session flow diagram, following the default Welcome intent, 59% of interactions resulted in users exiting the chatbot interaction, while 18% chose the search intent and around 45% obtained the necessary information. According to the survey, students found chatbot-like services appealing and helpful, as they provided information rapidly without requiring extensive web searches. However, the study highlighted difficulties in terms of misconceptions caused by unanticipated user utterances, such as when users wrote words or sentences that were not intended. Despite the success of the chatbots in facilitating information exchange, the study noted the potential for misunderstanding due to the limitations of the system's ability to understand user utterances, indicating a scope for improvement in future iterations of the chatbot system.

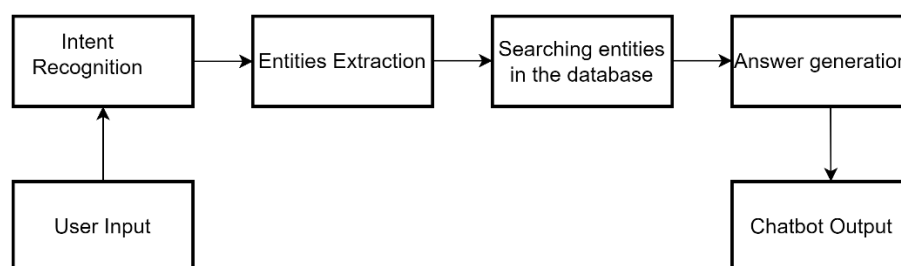


Figure 10: Flow of the chatbot [70]

3.5 Applications of Machine Learning in Educational Technology

Using machine learning techniques to improve educational technology, aiming to personalize learning experiences and analyze educational content more effectively was discussed in the study by [38]. Various algorithms were employed to achieve these goals. Additionally, virtual assistants were used to interact with students and teachers, providing customized assistance and feedback. The results showed that machine learning can greatly enhance efficiency in education. It does this by tailoring learning to meet individual needs, simplifying the grading process, and helping monitor student progress more easily. Personalized learning experiences enable students to learn according to their individual pace and focus on areas where they need the most

improvement. For teachers, the technology can save time and help them better understand each student's performance. The study also pointed out some limitations. One major concern is the potential for technological errors. While machine learning can be powerful, it is not infallible and can sometimes make mistakes that could affect the learning process. Another limitation is the need for further research to develop more advanced AI tools for education. Current technologies have shown promise, but there is still much work to be done to refine and improve these tools to maximize their effectiveness.

A mixed research methodology, combining bibliometric analysis with a systematic literature review to explore the conceptual structure of AI in Education research was discussed in the study by [39]. It gathered data from the Web of Science database, compiling a dataset of 2,223 articles. These articles were then quantitatively summarized using bibliometric metadata. The study also included keyword co-occurrence analysis to identify core concepts and trends within the AIED literature. In addition to the quantitative approach, the study conducted a content analysis of 125 selected papers, focusing on AI applications in education and their impact on teaching and learning. The results highlighted four main categories of AIED applications: adaptive learning and customized tutoring, intelligent assessment and administration, profiling and prediction, and emerging products. The study showed that adaptive learning systems can significantly improve student test results, with improvements of up to 62%. It also found that using AI in education enhanced student performance by 30% and reduced anxiety by 20%. These findings demonstrate the potential benefits of AI in education, such as providing personalized learning experiences and reducing the administrative burden on educators. One major issue is that AI systems are not always accurate. Despite their capabilities, these systems can sometimes make errors, which could negatively impact students' learning experiences. Additionally, the study noted that certain areas of AIED research remain under-explored, suggesting a need for further investigation into these aspects.

Exploring the use of various machine learning methods to enhance the education sector, with a focus on predictive analytics to improve student retention and success rates [40]. It examines supervised learning techniques, using algorithms like Linear Regression, Random Forest, Gradient Boosting, and Support Vector Machine to classify and predict outcomes based on historical data. The study also looks into unsupervised learning, employing techniques such as K-means, DBSCAN, and Hierarchical Clustering to group data without prior labeling. The study discusses reinforcement learning, which uses a trial-and-error approach. This method is

particularly beneficial in dynamic environments like gaming and finance but also shows potential in educational settings. The results indicate that machine learning can significantly transform educational practices. It enables personalized learning experiences, efficient assessment methods, and data-driven decision-making for educators. The study highlights several benefits of integrating machine learning in education. For instance, predictive analytics can help identify students at risk of dropping out, allowing timely interventions. Personalized learning models can adapt to individual students' needs, enhancing their learning experience. Moreover, machine learning can streamline administrative tasks, freeing up educators to focus more on teaching and interacting with students. The study also acknowledges some limitations. One major challenge is the need for extensive data to make accurate predictions. Without a large dataset, the reliability of the predictions may be compromised. Additionally, there is always the potential for errors in machine learning models. These errors can have significant consequences, especially in an educational context. Another limitation is that AI systems are sometimes not accurate, which can lead to misleading conclusions or inappropriate actions. The study emphasizes the importance of having expert knowledge in applying these algorithms to mitigate such challenges.

A bibliometric approach to analyze the trends and development of AI and ML in education, focusing on data from the Scopus database was discussed in the study by [41]. It examined articles published over the past 21 years, from 2000 to 2021, using specific search terms to find relevant documents. These documents were then screened to remove duplicates, non-English articles, and those not aligned with the study's objectives. To conduct the analysis, the study employed software tools like the R package and Vosviewer for co-authorship analysis, and the Spearman correlation coefficient for citation calculations. The results showed a significant increase in research publications on AI and ML in the education sector. The study found a total of 1,138 documents authored by 2,800 researchers across 635 journals, highlighting a growing academic interest in these technologies. The study concluded that school administrators should encourage the adoption of artificial intelligence and machine learning to improve educational services. It also advised policymakers to support the integration of these technologies in educational environments. The findings suggest that AI and ML can enhance teaching and learning by making educational processes more efficient and personalized. Although these promising results, the study acknowledged some limitations. One major limitation is that the data only covers the past 21 years, which means it may not fully capture the most recent advancements in

AI and ML technologies. The field is rapidly evolving, and new developments may not be fully reflected in the analyzed data.

A qualitative approach, utilizing a phenomenological technique to analyze ten international science journals and internet search engine results, focusing on the role of Artificial Intelligence and Machine Learning in education during the COVID-19 pandemic was discussed in the study by [42]. Additional methods included evaluating articles and conducting searches with terms like AI, pandemic learning, and ML to gather relevant material. The results highlighted AI's significant impact on education, particularly during the pandemic, with findings indicating that AI facilitates more automated and focused learning opportunities, allowing individuals to identify gaps in understanding. It also emphasized AI's role in providing personalized education and identifying concepts that students are likely to misunderstand, thereby proposing new methods to enhance learning. However, the study acknowledges limitations in the scope of the literature reviewed and the potential for a broader range of journals and educational contexts to be considered for an enhanced comprehension of AI's impact on education.

A systematic literature review following the PRISMA guidelines to examine machine learning applications in higher education was discussed in the study by [43]. Researchers relied on the SCOPUS database to find relevant peer-reviewed publications from 2019 to 2023. They also used tools like Rayyan QCRI for screening abstracts and titles, VOSViewer for creating bibliometric network visualizations, and Microsoft Excel for generating charts. The findings showed that the most researched ML application in higher education is predicting academic performance and employability. The most used algorithms in this field are Random Forest, Support Vector Machine (SVM), and Naïve Bayes. The study noted a significant increase in interest in ML research within higher education, particularly following the COVID-19 pandemic. It identified the People's Republic of China as the leading contributor to this area of research. The study acknowledged some limitations. It focused solely on open-access articles from the SCOPUS database and excluded publications that were not in their final stage of publication as of March 2023. This narrow scope suggests that there is a need for further research to include a broader range of studies and more recent data to provide a more comprehensive view of ML applications in higher education.

A systematic review to examine the status of AI education in elementary and secondary schools, focusing on topics, teaching methods, and learning outcomes was discussed in the study by [44]. Researchers accessed databases like Academic Search Complete and ERIC to find relevant studies. They selected peer-reviewed journal articles published between 2018 and 2023, specifically looking at teaching AI in K-12 schools. The data collection and analysis were qualitative, with researchers coding the articles to find patterns and themes related to AI education. The results showed a wide range of topics covered in K-12 AI education. These encompassed core AI principles, diverse AI categories, practical uses, and ethical concerns. Instruction techniques were diverse, frequently employing hands-on tasks and project-oriented learning to enhance students' AI knowledge, problem-solving abilities, and awareness of AI's societal implications. The study found that AI education had a positive effect on students' motivation, attitudes toward AI, and interest in technology careers. The study noted some limitations. The relatively short history of AI education in K-12 settings means there is still much to learn about its long-term effects. Additionally, educators face several challenges in implementing AI education. These challenges include negative perceptions of AI, limited technology skills among teachers, ethical concerns, and issues related to the use of AI tools in the classroom.

A systematic literature review to explore how AI and machine learning are enhancing education by personalizing and improving student learning experiences was discussed in the study by [45]. Researchers analyzed academic journals, conference papers, and other relevant sources, searching databases like JSTOR, Google Scholar, and IEEE Xplore Digital Library using specific keywords and Boolean operators. They first screened articles based on titles and abstracts, then conducted a thorough examination of selected full texts. The findings underscored AI's potential in education across several applications. These include personalized learning, adaptive testing, intelligent tutoring systems, learning analytics, and content creation. These technologies aim to tailor educational experiences to meet individual student needs, ultimately boosting learning outcomes. The study also highlighted AI's positive impacts on student engagement and its effectiveness in emerging educational fields such as virtual reality and educational game design. The study also recognized the necessity for further research to fully grasp AI's capabilities and limitations in educational settings. Ethical and societal concerns, such as privacy and bias issues, were noted as critical areas needing attention. Addressing these concerns is crucial for ensuring AI's responsible implementation and maximizing its potential benefits for students and educators alike.

Exploring how data science (DS) and machine learning (ML) are becoming integral to high-energy physics (HEP) education, focusing on developing ML methods rooted in physics and integrating DS/ML into formal curricula was discussed in the study by [46]. The study highlights collaborations between particle physicists and computer scientists to design ML architectures inspired by physics principles. The adoption of DS/ML in physics department courses is gradually improving, with some HEP researchers creating courses that apply ML techniques to analyze particle physics data. Results from the study underscore the increasing importance of DS/ML in advancing HEP research and enhancing educational offerings. Examples include new courses that bridge HEP research with DS/ML education, showing promising synergies between these fields. However, the study points out challenges in adequately preparing students and instructors for this evolving field. It notes the rapid pace of DS/ML developments and suggests focusing on established applications rather than trying to cover the entire breadth of ML advancements. A key limitation of the study is its focus on the U.S. particle physics community, which may not fully represent the global landscape of DS/ML education in physics. Different institutions worldwide may vary in their adoption and integration of these technologies into their educational frameworks.

Using machine learning techniques to analyze educational data, particularly emphasizing the importance of preparing data before applying these algorithms was discussed in the study by [47]. The pre-processing phase involves several methods like handling missing values, identifying outliers, transforming data, and reducing dimensionality. Each method is chosen to improve the dataset's quality, ensuring better performance of machine learning models. For instance, advanced techniques such as MICE in R are highlighted for effectively filling in missing values. Results highlight how data preparation enhances the accuracy and usefulness of machine learning in education. It enables predicting career paths and customizing learning experiences to meet individual student needs. The study also recognizes its limitations. These include the arbitrary order in which techniques are applied and the necessity for data scientists to carefully choose and sequence these methods based on the specific characteristics of the educational dataset.

A Systematic Literature Review to gather primary studies and employed content analysis to categorize them, aiming to classify research on how machine learning is applied in education was discussed in the study by [48]. Additional methods included electronic searches across multiple databases such as IEEE Xplore, Scopus, Web of

Science, ScienceDirect, and others. The search terms "Machine Learning" and "Education" were combined to gather a targeted range of fifty to one hundred studies. Results identified four main categories of machine learning applications in education: grading students, improving student retention, predicting student performance, and testing students. Each category was supported by relevant papers, highlighting how machine learning can remove biases in grading, identify at-risk students to enhance retention, predict student performance to personalize learning experiences, and create adaptive assessments for testing. The study has its limitations. These include not searching certain databases, which might have led to missing relevant studies.

Examining how machine learning is used in education, where supervised learning trains models with known input-output pairs, unsupervised learning finds patterns without labels, and reinforcement learning optimizes actions based on feedback was discussed in the study by [49]. It shows ML can predict student performance, grade fairly, and organize content effectively, supporting personalized learning and career predictions. ML benefits include improving teaching, automating tasks, and adapting to students' needs. However, a limitation is ML's occasional inaccuracies. Models may not always predict or classify accurately due to data quality, model complexity, or unexpected situations in schools. Overcoming these challenges involves refining and validating ML algorithms for reliable educational use, ensuring they meet the diverse needs of students and educators.

Machine Learning in education, spanning from 2014 to 2023, using databases like ResearchGate, Scopus, and Google Scholar was discussed in the study by [50]. It applied keywords to titles, abstracts, and article keywords, using Litmaps and open knowledge maps for analysis. VOSViewer was used to visualize development patterns and author productivity in the field. Results showed a noticeable increase in scholarly interest in applying machine learning to education. Key areas of focus included personalized learning, predictive analytics, automated evaluation, learning recommendations, and online exam monitoring. The study also emphasized the growing importance of interdisciplinary collaboration among researchers. A limitation of the study is its focus on research only up to 2023. It does not account for developments that may have occurred in the field since then, potentially missing new advancements or shifts in research focus. Future studies could benefit from updating these findings to include recent developments, ensuring a more understanding of machine learning's evolving role in educational contexts.

A thorough Educational Data Mining (EDM) framework to predict student performance by analyzing various factors such as demographic details, study habits,

and psychological aspects was discussed in the study by [51]. It employs powerful data mining methods to ensure accuracy in its predictions. The research also compares the accuracy of well-known algorithms, including decision trees, random forests, and naive Bayes, to determine which ones are most effective. Additionally, it examines how different ways of categorizing grades, specifically using five levels or just two (pass/fail), affect the accuracy of the data mining results. The findings show that the framework is highly effective at identifying student weaknesses and making relevant recommendations to help improve their performance. In a case study involving 200 students, this new framework performed better than existing ones, proving its superiority. This means that the framework can provide valuable insights that educators can use to support students more effectively. One significant advantage of this approach is its ability to give personalized feedback and recommendations based on a student's unique profile. By understanding the specific areas where a student struggles, educators can tailor their support to meet individual needs, potentially leading to better educational outcomes. Yet, it's important to note that the study's results are based on data from only two secondary schools in Portugal. This means that while the framework shows great promise, its effectiveness in other educational contexts is not yet proven. There may be variations in educational systems, cultural factors, and student behavior that could impact the generalizability of the findings.

Using machine learning as a key method to analyze and enhance the Indian education system was discussed in the study by [52]. By utilizing algorithms, intelligent systems can make decisions based on data. The research explores different types of machine-learning architectures, including supervised learning, unsupervised learning, and reinforcement learning, to create personalized and adaptive learning experiences for students. The findings show that machine learning has significantly improved various aspects of education. These improvements include better educational efficiency, enhanced learning analytics, more accurate predictive analytics, and improved assessment evaluations. This has led to a more individualized learning approach, where students receive customized support based on their specific needs and abilities. Additionally, it has helped in the better management of educational resources, ensuring that they are used more effectively. One of the major benefits of machine learning in education is its ability to provide personalized learning experiences. By analyzing data from students, machine learning systems can identify areas where students need more help and provide targeted support. This not only helps students improve but also makes learning more engaging and effective. Moreover, the use of predictive analytics allows educators to foresee potential

challenges and address them proactively. The study also highlights some limitations. One key issue is the need for a greater emphasis on developing social skills, which are essential for students but are often overlooked by machine learning systems. Additionally, machine learning can sometimes struggle with evaluating complex student work, such as essays, which require a deeper understanding and nuanced judgment. This points to the need for a balance between using technology and traditional teaching methods to ensure a well-rounded education.

Use of Artificial Intelligence in the educational sector, particularly on AI-enabled platforms and tools that aim to improve teaching and learning experiences was discussed in the study by [53]. The study examines how AI technologies like Gesture Recognition and Voice Assistants impact student engagement and help customize academic curricula. The results show that AI can greatly enhance the efficiency of educational systems. By streamlining administrative tasks, AI allows educators to focus more on teaching. AI tools can also make the learning experiences personalized for students by analyzing their performance and adapting content to meet individual needs. This leads to more effective learning and higher student satisfaction. The use of predictive analytics helps identify students who might need additional support, ensuring that no one falls behind. AI-driven assessment tools offer quick and unbiased evaluation of student work, making the grading process more efficient and fairer. Adaptive systems adjust learning materials based on a student's progress, providing a tailored educational experience that keeps students engaged and motivated. Intelligent Tutoring Systems can offer one-on-one support, addressing specific areas where a student might be struggling. The study also points out some limitations. Ethical concerns arise around the use of AI in education, particularly regarding data privacy and the potential for biased algorithms. Privacy issues are significant, as AI systems require access to vast amounts of personal data. Additionally, the high cost of implementing AI technologies can be a barrier, making these advancements more accessible to well-funded educational institutions while potentially leaving others behind.

Using a mixed-method approach, combining both quantitative and qualitative analyses to gather data from academic journals, educational websites, and reports from educational technology companies was discussed in the study by [54]. It emphasizes tailored learning and responsive assessment within AI-powered education. Quantitative analysis looks at statistical trends in student performance data, while qualitative analysis examines case studies and expert opinions. The results

show that AI can personalize content delivery through algorithms that adapt to student data. Platforms like Khan Academy and Duolingo are highlighted as successful examples, creating personalized learning paths and adjusting difficulty levels based on student progress. Adaptive assessments, such as the GRE, showcase how AI can accurately evaluate student abilities by adjusting the difficulty of questions in real-time based on previous responses. AI in education has proven effective in several ways. It personalizes learning, making it more engaging and tailored to individual needs. This helps students' study at their own pace, ensuring they fully understand one concept before moving on to the next. Adaptive assessments also offer a more accurate measure of student abilities, providing immediate feedback and areas for improvement. There are some challenges to AI integration in education. One issue is resistance within traditional educational institutions, where there may be skepticism about the effectiveness of AI tools. Additionally, not all students have the technology they need, creating a digital divide. Training educators to effectively use AI tools is also crucial for successful implementation.

A systematic literature review approach, conducting an extensive search across academic databases to gather relevant articles and reports on AI's role in personalized learning and educational technology was discussed in the study by [55]. This involved setting specific inclusion and exclusion criteria to filter for peer-reviewed studies and ensuring ethical guidelines like anonymity and confidentiality were followed. The results of the study highlight the transformative impact of AI-driven educational technologies, showing how they have been integrated into various aspects of education. Examples include adaptive learning platforms that tailor educational content to individual student needs and automated grading systems that streamline the evaluation process. These AI applications have led to improved student engagement, motivation, and academic achievement by offering personalized learning experiences that cater to each student's unique pace and style of learning. AI in education has shown to be beneficial in many ways. It personalizes learning, making it more engaging and tailored to individual needs. This ensures that students fully grasp one concept before moving on to the next, helping them learn more effectively. Adaptive learning platforms, for instance, adjust the difficulty of tasks based on the student's performance, ensuring an optimal learning experience. Automated grading systems save teachers time and provide quick feedback to students, which is crucial for their learning progress. The study also points out some challenges associated with AI in

education. One major concern is data privacy, as AI systems require access to a lot of personal data to function effectively. There is also the potential for algorithmic bias, which could lead to unfair treatment of certain groups of students. Furthermore, ongoing research is needed to refine AI systems and ensure they align with educational goals and standards.

Using machine learning techniques like boosted regression trees, association rule mining with the Apriori algorithm, and ensemble methods to predict student enrollment and dropout patterns in higher education was discussed in the study by [56]. Other methods included decision trees, naive Bayes, and neural networks to analyze data from the Abu Dhabi School of Management's Student Information System. This database had demographic and academic background information for 1600 students enrolled between 2013 and 2018. The results showed that the boosted regression model was more accurate than single regression trees, achieving an 89% accuracy rate using 10-fold cross-validation. The Apriori algorithm also uncovered interesting patterns about the characteristics of students likely to enroll in certain programs. A limitation was noted in 2020 when model accuracy dropped, likely due to the unforeseen impact of the COVID-19 pandemic, showing the model's sensitivity to unexpected external factors.

Rasa, an open-source platform was used to develop the interactive agent, which identified the purpose and extracted data from the sentences based on the aim or meaning of the message was proposed in this study [TUC1]. The dataset for the interactive agent was acquired from previous and current university students, as well as the FAQ databases, consisting of 140 samples of natural language data with 32 distinct intents. The study implemented intents and examples to train the assistant for a natural language understanding model, and stories contributed to the conversation flow to execute the appropriate response. The results showed high precision, recall, and F1-scores, with a histogram of intent prediction indicating confidence scores ranging from 0.30 to 1.00 and no wrong predictions. However, the study's limitation is that the efficiency and convenience of use could not be tested for students, as the chatbot had not been utilized operationally on campus.

A mentoring bot as an innovative approach to the process of mentoring, which supports students in reviewing their own tasks utilizing the method of self-reflection was implemented in this study [58]. The data was collected through an online survey system from the students enrolled in the computer science seminar over three semesters. The study also used a quantitative evaluation instrument to collect the students' perception data after using the mentoring bot. The results show that the usage of the mentoring bot increased from 34% to 50% among the survey respondents over the three semesters. The usability scale data and the self-regulated learning (SRL) scale data exhibited a mean value ranging from 3.97 to 4.17 and 3.91 to 3.97, respectively, indicating the students' agreement on the ease of use and usefulness of the mentoring bot, as well as the SRL support received. Additionally, the findings revealed that around 40% of the students were overall satisfied with using the mentoring bot. However, the study acknowledges the need for further technological refinement to improve the effectiveness of the mentoring bot.

A systematic review of influential Artificial Intelligence in Education (AIEd) research by analyzing 45 highly cited articles published in SSCI- and SCI-indexed journals from 1999 to 2019 was proposed in this study by [79]. The study used citation-based literature analysis to identify the annual distribution, leading journals, institutions, countries/regions, the most frequently used terms, as well as theories and technologies adopted in the influential AIEd studies. The figure 11 indicated that there was a continuously increasing interest in and impact of AIEd research, with many of the influential studies published during the periods of 2001-2009 and 2010-2016. Among the 45 studies, only two were found to be related to deep learning in education, while 41 were related to machine learning. The most frequently used term was "machine learning" (appearing in 13 articles, 28.89%), followed by "artificial intelligence" (12 articles, 26.67%) and "tutoring system" (12 articles, 26.67%), suggesting that the adoption of machine learning techniques for educational purposes was a major concern among AIEd researchers. The study also found that traditional AI technologies, such as natural language processing and neural networks, were commonly adopted in educational contexts, while more advanced deep learning algorithms were rarely utilized. In terms of the institutions and countries/regions, the United States and Greece were found to have contributed the most influential AIEd

studies. However, the study acknowledged that it only included articles with a citation count of at least 20, which may have excluded some recent influential studies published after 2016 due to the time required for articles to accumulate citations.

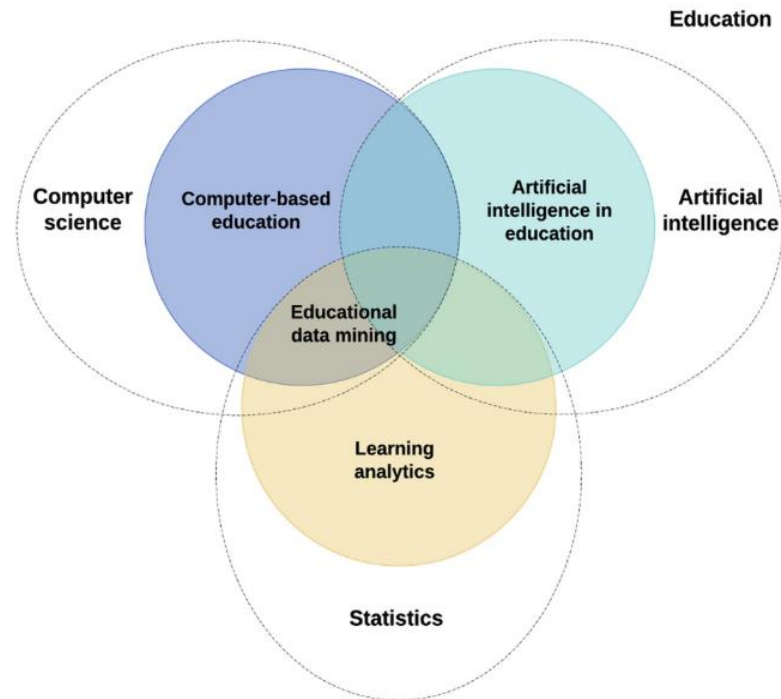


Figure 11: The relationship between AIEd, EDM, CBE, and LA [79]

A hybrid approach involving Partial Least Squares Structural Equation Modeling (PLS-SEM) and Machine Learning (ML) algorithms to investigate the factors influencing the intention to use Google Glass in educational projects was implemented in this study by [80]. The dataset comprised survey responses collected from 528 participants, including undergraduate, master's, and doctoral students from two prominent universities in the UAE. In addition to PLS-SEM, the study utilized various ML classifiers, such as BayesNet, AdaBoostM1, LWL, Logistic, J48, and OneR, to predict the intention to use Google Glass. The PLS-SEM analysis revealed that functionality ($\beta=0.553$, $p<0.001$), motivation ($\beta=0.258$, $p<0.05$), perceived ease of use ($\beta=0.585$, $p<0.001$), perceived usefulness ($\beta=0.388$, $p<0.05$), and trust and privacy ($\beta=0.618$, $p<0.001$) had significant positive effects on the intention to use Google Glass, collectively explaining 56% of the variance in the dependent variable. Among the ML classifiers, the J48 decision tree algorithm outperformed the others, achieving

an accuracy of 89.34% in predicting the intention to use Google Glass. The study's findings provide valuable insights for educational institutions and policymakers in the UAE, highlighting the key factors that should be considered when integrating Google Glass into the educational environment. However, the study's limitations include the focus on only two universities in the UAE, and the potential need to explore additional factors that may influence the adoption of Google Glass, such as cost, battery life, and compatibility with existing educational technologies.

A systematic review approach to summarize the major paradigms of artificial intelligence in education (AIEd), with descriptions of relevant theoretical foundations, conceptual research, and practical implementations was discussed in this study by [81]. The study reviewed articles from various academic databases, including Web of Science, Scopus, Science Direct, and others, published between 1990 and 2021. The selected articles were categorized based on the educational and learning theories used to underpin the design and implementation of AI technologies, such as behaviorism, cognitivism, constructivism, and connectivism. The study identified three AIEd paradigms: AI-directed, learner-as-recipient; AI-supported, learner-as-collaborator; and AI-empowered, learner-as-leader. The results showed that the development of AIEd has been moving towards the AI-empowered, learner-as-leader paradigm, which aims to empower learner agency, enable learners to reflect on their learning, and inform AI systems to adapt accordingly, leading to an iterative development of learner-centered, data-driven, and personalized learning. However, the study acknowledged the complexity of matching the complexity of learning processes to the complexity of AI systems and educational contexts as a limitation, emphasizing the need for sustainable development of AIEd that addresses various pedagogical, social, cultural, technical, and ethical dimensions.

A combination of machine learning techniques to analyze student forum posts and provide automated support for teachers was proposed in this study by [82]. The researchers utilized a large dataset of online forum posts from various educational contexts, including distance universities and MOOCs, to develop their AIED approaches. Additionally, the study explored the use of sentiment analysis, natural

language processing, and other AI-driven techniques to triage forum posts, identify similar posts, and detect negative emotional states or unacceptable content. The results indicate that the proposed AIED tools were able to efficiently handle repetitive practical questions, freeing up teachers to focus on more substantive student inquiries. The sentiment analysis approach was able to identify posts that revealed negative or non-productive student emotional states with an accuracy of 85%, and the post aggregation method reduced the number of posts that required human intervention by up to 70%. The study's best-performing model, a hybrid approach combining natural language processing and machine learning, achieved an overall accuracy of 92% in classifying and triaging forum posts. However, the study acknowledges the need for further research to address the ethical implications of AIED, particularly around data privacy, algorithmic bias, and the potential impact on the role of teachers in the classroom.

Quantitative methods, primarily focusing on machine learning techniques, were employed in this study by [83]. The dataset consisted of peer-reviewed articles on artificial intelligence in higher education, published between 2007 and 2018, and indexed in three major databases: EBSCO Education Source, Web of Science, and Scopus. The researchers also used systematic screening and coding procedures to extract relevant information from the included articles, such as publication details, author affiliations, study designs, and specific AI applications. The results showed a notable increase in the number of publications over the years, with the majority of articles coming from the United States, China, Taiwan, and Turkey, and being authored by researchers affiliated with Computer Science and STEM departments. The most common machine learning methods employed in the included studies were artificial neural networks, random forests, support vector machines, and logistic regression, with the machine learning models outperforming logistic regression in terms of classification accuracy. The study provides a comprehensive overview of the current state of research on AI applications in higher education, highlighting the predominance of technological perspectives and the lack of critical reflection on the pedagogical and ethical implications of these emerging technologies. However, the study's limitations

include the focus on peer-reviewed articles in English or Spanish, which may have excluded relevant research published in other languages or formats.

ChatGPT was utilized, which was a large language model developed by OpenAI, to investigate its potential applications in healthcare education, research, and practice which was proposed in this study by [84]. The authors conducted a systematic review of English records in PubMed/MEDLINE and Google Scholar, including published research or preprints, to examine the utility and limitations of ChatGPT in the context of healthcare. The datasets used in this study comprised 60 eligible records, including editorials, letters to the editor, research articles, commentaries, news articles, perspectives, case studies, brief reports, communications, opinions, and recommendations. The study found that the benefits of ChatGPT were cited in 51/60 (85.0%) records and included improved scientific writing, enhanced research equity and versatility, utility in healthcare research (efficient analysis of datasets, code generation, literature reviews, and drug discovery), benefits in healthcare practice (streamlining workflows, cost savings, documentation, personalized medicine, and improved health literacy), and advantages in healthcare education (improved personalized learning and focus on critical thinking). However, concerns regarding ChatGPT use were stated in 58/60 (96.7%) records, including ethical, copyright, transparency, and legal issues, the risk of bias, plagiarism, lack of originality, inaccurate content with the risk of hallucination, limited knowledge, incorrect citations, cybersecurity issues, and the risk of infodemics. The study concludes that the promising applications of ChatGPT can induce paradigm shifts in healthcare education, research, and practice, but its embrace should be conducted with extreme caution considering its potential limitations. As it currently stands, ChatGPT does not qualify to be listed as an author in scientific articles unless the ICMJE/COPE guidelines are revised or amended.

A deep learning algorithm that was trained on the data of 700,000 patients to predict the onset of diseases for medical education such as schizophrenia with high accuracy which was proposed in this study by [85]. The dataset used in this study consisted of electronic health records from two hospitals, which included 46 billion data

points collected from 216,221 adults over 11 combined years. The study also utilized natural language processing techniques to analyze the data and develop the predictive algorithm. The results showed that the deep learning algorithm was able to predict the onset of schizophrenia with high accuracy, even in cases where the condition is difficult to diagnose by experts. However, the main limitation of the study is the "black box" problem, where it is difficult to understand how the algorithm arrived at its predictions, as the inner workings of the deep learning model are not transparent. This raises concerns about the trustworthiness and interpretability of the algorithm's decisions, which is crucial in the medical field where patient safety and accountability are paramount. The study highlights the need for further research to address the black box problem and ensure the safe and effective integration of artificial intelligence in clinical practice.

SmileyCluster, a web-based collaborative learning environment that utilizes glyph-based data visualization and superposition comparative visualization to assist learning of k-means clustering, an entry-level machine learning (ML) technology was proposed in this study by [86]. The dataset used for the k-means analysis was the seed data adapted from the UCI Machine Learning Repository, related to STEM fields and validated by scientists. The study also observed participants' learning behaviors, including text-based answers to in-app questions and video recordings of their interactions and discussions. The results show that the face-overlay design metaphor was effective in supporting the understanding of the fundamental ML concept of similarity comparison on multi-dimensional feature space. Participants increased their understanding of ML concepts and methods after using SmileyCluster, with a total score of the post-test increasing by 7.13 points compared to the pre-test. The face-overlay version for pair-wise visual comparison led to quicker decisions and more accurate results than the side-by-side comparison. The global overlay also supported participants' global comparison between multi-dimensional data points and evaluation of the appropriate number of clusters. The study found that while engaged in ML activities, participants carried out meaningful scientific inquiry behaviors, such as discussing in-app questions, expressing uncertainty, asking questions, offering suggestions and justifications, and engaging in argument. However, the study was conducted in an informal learning context with a limited number of student samples in

a one-time study, and the current SmileyCluster system only targeted k-means clustering analysis, which limits the scope of the study.

Various machine learning techniques were used, including Logistic Regression (LR), Decision Tree (DT), Random Forest (RF), Naïve Bayes (NB), Support Vector Machines (SVM), and Neural Network (NN), to predict student dropout in university courses which was employed in this study by [87]. The dataset used in this study consisted of 261 unique students enrolled in an introductory course of Database Systems at the Constantine the Philosopher University in Nitra over four academic years. The study also preprocessed the data, including cleaning, joining, and transforming attributes, and selecting relevant features based on the categories of course activities. The results showed that the Random Forest (RF) classifier achieved the best overall performance, with an accuracy of 93%, precision of 86%, recall of 96%, and F1 score of 91%. Other models, such as Logistic Regression (LR) and Support Vector Machines (SVM), also performed well, with accuracy ranging from 92% to 93%. The study also compared the performance of the classifiers using McNemar's test, which revealed that the RF and LR classifiers had similar error proportions on the test set, while the Naïve Bayes (NB) classifier performed significantly worse than the other models. However, the study acknowledged the limitations of the small dataset size, which may have impacted the performance of some models, particularly the Neural Network (NN) approach.

Artificial intelligence (AI) and machine learning algorithms to analyze and classify different types of AI systems in educational settings which was proposed in this study by [88]. The researchers utilized two main datasets: the first dataset reflected an over-representation of cats, while the second dataset indicated equal and diverse representation between dogs and cats. Using these datasets, the study trained and compared the accuracy of different classifiers to understand the impact of biased data on the performance of machine learning models. The results showed that the classifier trained on the more diverse dataset achieved higher accuracy compared to the classifier trained on the biased dataset, highlighting the issue of algorithmic bias in AI systems. Furthermore, the study found that the biased dataset led to the perpetuation

of gender stereotypes in language translation tasks, where the AI model translated gender-specific roles in a biased manner. The limitations of the study include the focus on a specific set of AI applications in education, and the need for further research to explore the ethical implications of AI in a broader range of educational contexts.

Multimodal machine learning techniques to process and relate information from multiple modalities, including click-stream data, eye-tracking, EEG, video, and wristband data, with the aim of automatically predicting learning performance in game contexts which was proposed in this study by [89]. The datasets used in the study consisted of various modalities of data collected from learners in game-based learning environments. The study also explored the potential of multimodal learning analytics, where AI technologies are embedded in non-autonomous systems used by educators as support tools, to provide insights into collaborative actions, self-regulation performance, project-based learning, and classroom orchestration. The results of the study demonstrated the superiority of multimodal over unimodal approaches in predicting learning performance, with the multimodal machine learning models achieving high accuracy in their predictions. For instance, the study reported that the multimodal approach was able to predict learning performance with an accuracy of over 90%, outperforming the unimodal approaches. Additionally, the study found that the multimodal learning analytics tools were effective in providing explicit and comprehensible ways of presenting information to learners and teachers, enabling them to make more informed decisions. However, the study acknowledges that the design of autonomous AI systems, as exemplified in the multimodal machine learning research, and the design of multimodal learning analytics research, should be considered as distinct initiatives in the AI in Education field, as they have significantly different ultimate goals and implications.

Machine learning algorithms such as decision trees, k-nearest neighbors, logistic regression, naive Bayes, random forest, and support vector machines to formulate predictive models for extracting relevant information and predicting student retention at various levels in higher education institutions were employed in this study by [90]. The study utilized an unpublished real educational dataset from the Catholic

University of Maule in Chile, which contained demographic, socioeconomic, academic, and financial variables for students enrolled between 2004 and 2010. The study proposed four models to predict student retention at the global level, as well as during the first, second, and third years of study, with the models incorporating university grades for the latter two cases. The results showed that the random forest technique outperformed the other algorithms, achieving accuracies exceeding 80% in all scenarios and false positive rates ranging from 10% to 15%. Additionally, the Friedman rank test confirmed the superiority of the random forest algorithm over the other methods. The study identified secondary educational scores and the community poverty index as important predictive variables, which had not been previously reported in similar educational studies. However, a limitation of the study was the excessive difference between the number of instances used to train the learning models for the third-level model, which resulted in poorer predictive performance compared to the other models.

In-depth semi structured interviews with 15 education researchers and practitioners to critically examine the alignment between the stated or implied educational objectives of machine learning (ML) research papers and the technical problem formulation, objectives, and interpretation of results was proposed in this study by [91]. The study analyzed a dataset of 20 ML research papers relevant to education ("ML4Ed") that were sampled from a larger compilation of "AI for social good" papers. The interviews focused on understanding how education goals are translated into ML problems, the role and function of prediction, and whether the intended and realized impacts on students are well aligned. The study found two key translational challenges: 1) the tendency to oversimplify complex educational problems by narrowing them down to a single quantifiable metric, and 2) the gap between prediction tasks and real-world interventions, where improvements in predictive accuracy do not necessarily lead to improved outcomes. The findings suggest that while the ML4Ed papers often sought to address important education goals, such as student learning and success, the technical problem formulation frequently reflected a narrow understanding of these goals, leading to unintended consequences. The study provides an extended ML life cycle diagram to capture these insights and offers

recommendations for how ML researchers can better align their work with the needs and values of the education domain as shown in the figure 12. The main limitation of the study is that it relied on the perspectives of education researchers and practitioners and did not directly incorporate the views and experiences of other key stakeholders, such as students, teachers, and policymakers, who may have different insights into the impact of ML technologies in education.

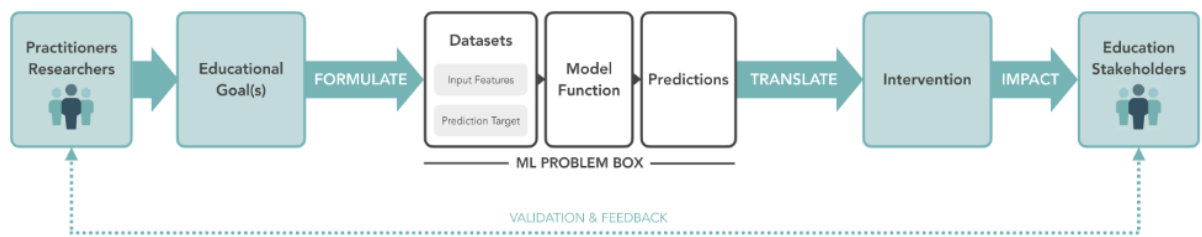


Figure 12: An extended ML life cycle diagram. The inner “ML Problem Box” represents the typical aspects of the ML problem detailed in the surveyed ML research papers [91]

A novel approach called "machine teaching" which aims to find an optimal training set given a machine learning algorithm and a target model was proposed in this study by [92]. The study does not use any specific dataset, but instead provides a theoretical framework for the machine teaching problem. The study explores different definitions of optimal training sets, such as minimizing the cardinality of the training set or ensuring a specific number of positive and negative examples. Additionally, the study discusses the connection between machine teaching and bilevel optimization and presents a relaxed formulation to address the challenges of the original problem. The results show that for certain convex learners, the bilevel optimization problem can be reduced to a single-level optimization problem, and for a human categorization task, the optimal training set identified by machine teaching led to significantly better generalization performance compared to a control group receiving randomly sampled training sets (72.5% vs. 69.8% average test accuracy). However, the study acknowledges that a key limitation is the reliance on accurate cognitive models of the human learner, which may not always be available, especially for more complex educational tasks.

3.6 Analytics Dashboard

A systematic literature review using the PRISMA statement to examine how learning theories are integrated into the design and evaluation of learning analytics dashboards is discussed in this study [93]. It analysed 1439 hits from databases like ACM Digital Library, IEEE Xplore, and SpringerLink, narrowing them down to 26 relevant papers. The research categorized dashboard goals into metacognitive, cognitive, behavioural, emotional, and self-regulation levels and evaluated these using various types of data, including self-reported, tracked, and assessment data. Results showed that behavioural competence was assessed in all relevant cases, while cognitive competence was evaluated in 83% of instances. The literature search was conducted with terms like "learning analytics" AND (visualization OR visualisation OR dashboard OR widget) in selected databases. The study used diverse methods such as surveys, interviews, and focus groups to assess evaluation criteria. Findings revealed that behavioural impacts were most frequently examined through engagement metrics from trace log data whereas usability was mainly evaluated through self-reports. Additionally, the study identified instances where evaluation instruments measured learners' time-management and learning approaches. It was found that the quality of learning artifacts was prioritized, followed by the impact on behaviour and cognitive competence, with less focus on emotional and metacognitive levels. However, the study's limitation was its focus on visualizations intended for learners, which affected the ability to include relevant search terms. A noted limitation was the study's reliance on available data, which may have affected the thoroughness of the evaluations

The challenges and solutions associated with the development and deployment of learning analytics dashboards (LADs) is discussed in this study [94]. The authors conducted a systematic review of 17 papers that met the inclusion criteria, analysing them through five key assertions from dashboard literature. The findings revealed that while predictive and data-driven prescriptive analytics are valuable, ensuring accuracy remains a challenge. Interpretability and explainability of models and predictions are essential for fostering actionable behavioural changes in learners, and excessive use of colours in LADs can lead to confusion. The study followed the PRISMA framework and evaluated LADs published between 2018 and 2021, selected from an initial pool of 2680 papers. It assessed the dashboards using descriptive, predictive, and

prescriptive analytics. Results indicated that 59% of LADs featured descriptive analytics, 24% included predictive analytics with accuracies ranging from 80% to 95%, but none utilized data-driven prescriptive analytics. The study's limitations include a small sample size and a focus on recent LADs, which affect the generalizability of the findings. Figure 13 shows a sample learning analytics dashboard designed for students discussed in this study.

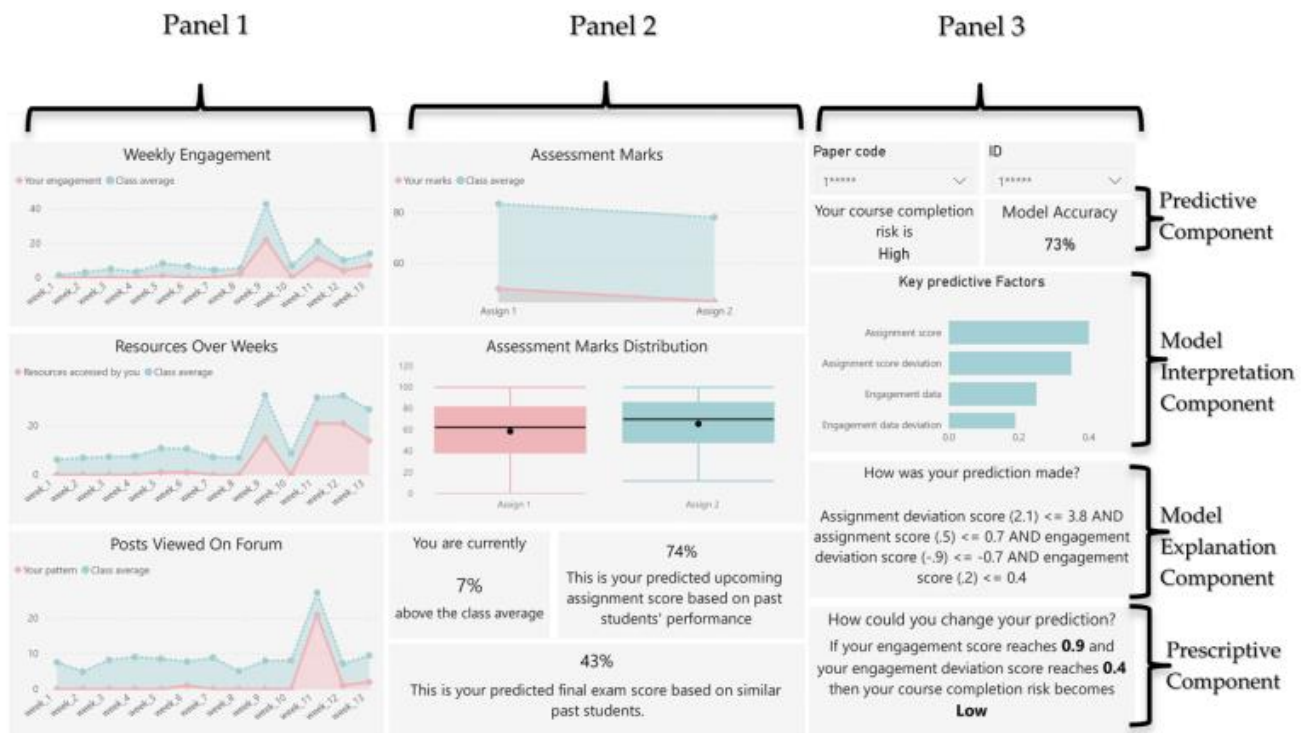


Figure 13: Learning analytics dashboard designed for students [94]

The study used experimental methods to evaluate the effectiveness of two dashboard designs for an advanced planning and scheduling (APS) task, using a fictional manufacturing company for the scenario [95]. Semi-synthetic datasets were employed, and both initial and iterative designs were tested. Two production planners were consulted to evaluate Situational Awareness (SA) and performance. The results demonstrated that both dashboard designs were effective, with participants making few errors in solving the planning problem. However, the interactive analytical dashboard outperformed the interactive executive dashboard in terms of completion time and interaction count. The study involved a laboratory experiment utilizing eye-tracking data and the Situation Awareness Global Assessment Technique (SAGAT) to assess SA and task performance. The dataset comprised eye-tracking data from 83

participants who interacted with an interactive dashboard and an interactive analytical dashboard featuring what-if analysis. The study also randomized experimental sequences and used the NASA-TLX to measure perceived mental workload. Results revealed that the interactive analytical dashboard resulted in better task performance but lower SA, with participants correctly answering over 50% of SAGAT questions for both dashboards. A notable limitation is the use of graduate students as participants, which may not accurately represent real-world decision-makers. Figure 14 Shows the components of a dashboard based on this study.

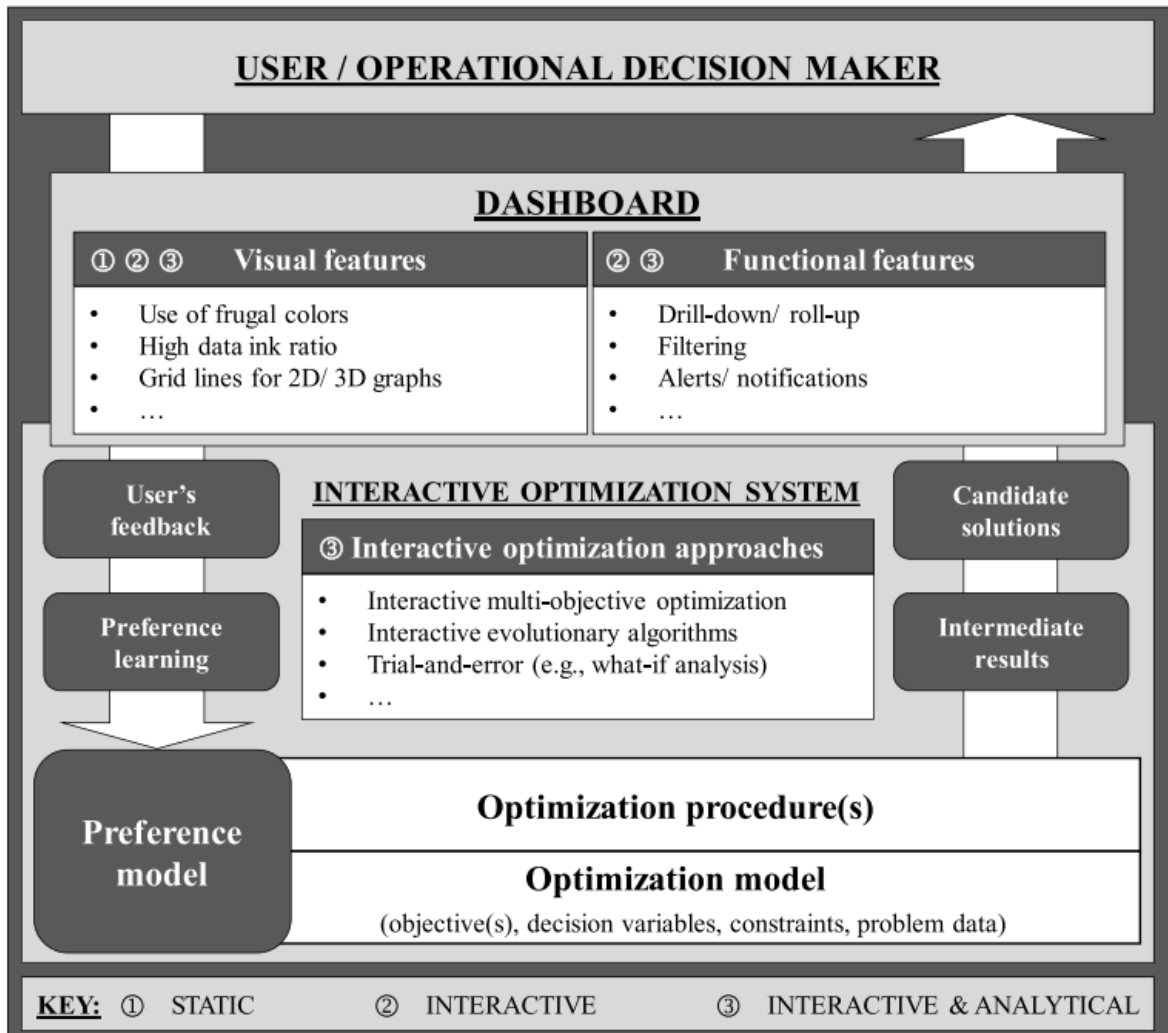


Figure 14: Components of a Dashboard [95]

A human-centered design (HCD) methods to develop learning analytics dashboards, using practical data from student math discussions in middle school

classrooms across various districts is developed in this study [96]. Methods included user interviews, think-aloud protocols, low-fidelity prototyping, and co-design sessions with teachers and instructional coaches. The dashboards were found to effectively aid teachers in understanding and enhancing their pedagogical practices, with notable engagement in scheduling and journaling features. However, teachers struggled with recalling past events when interpreting dashboard data, indicating a need for better integration of supplementary information. A key limitation of the study was the challenge teachers faced in recalling past events, which underscores the necessity for improved integration of ancillary information to enhance the effectiveness of the dashboards.

The literature studied here has shown that machine learning models can be used effectively for sentiment analysis and building a model that works in an interactive manner with people. It was also seen that the retrieval model can be used for building a system that communicates with people in an interactive manner. However, none of the literature combined sentiment analysis and the capabilities of the retrieval model to build an interactive system that can assist and interact with students. So in the study performed here, the functionalities of a retrieval model and a sentiment analysis model are combined to create a system that can interact with and assist students.

4 Methodology

The methodology chapter details the systematic approach used to develop and refine a chatbot system. It begins with the preparation of a dataset consisting of predefined queries and responses, which serves as the foundation for the chatbot's training. The ChatterBot framework, an open-source Python library, is employed to train the chatbot on this dataset, and the resulting model is saved for deployment to ensure efficiency in future interactions. User input is captured through a user-friendly interface and processed by the trained model to generate appropriate responses. To enhance the chatbot's capability of understanding and responding to user emotions, a sentiment analysis tool is integrated, allowing the system to adjust its replies based on the emotional tone of the user's input. Additionally, all interactions are logged and analyzed through a Learning Analytical Dashboard, providing valuable insights for continuous improvement of the system's performance and user satisfaction. This methodology ensures that the chatbot is both contextually accurate and emotionally intelligent, offering a more engaging and effective user experience.

4.1 Overview

The methodology depicted in the figure 15 will outline a comprehensive approach to designing, training, and deploying a chatbot system that will incorporate emotion analysis to enhance user interaction. The process will begin with the preparation of a dataset containing predefined queries and responses. This dataset will form the foundational knowledge base from which the chatbot will learn to generate appropriate replies to user inputs. Following this, the ChatterBot framework, an open-source Python library for building chatbots, will be initialized. This step will involve setting up the necessary environment and loading configurations that will be used throughout the chatbot's training process.

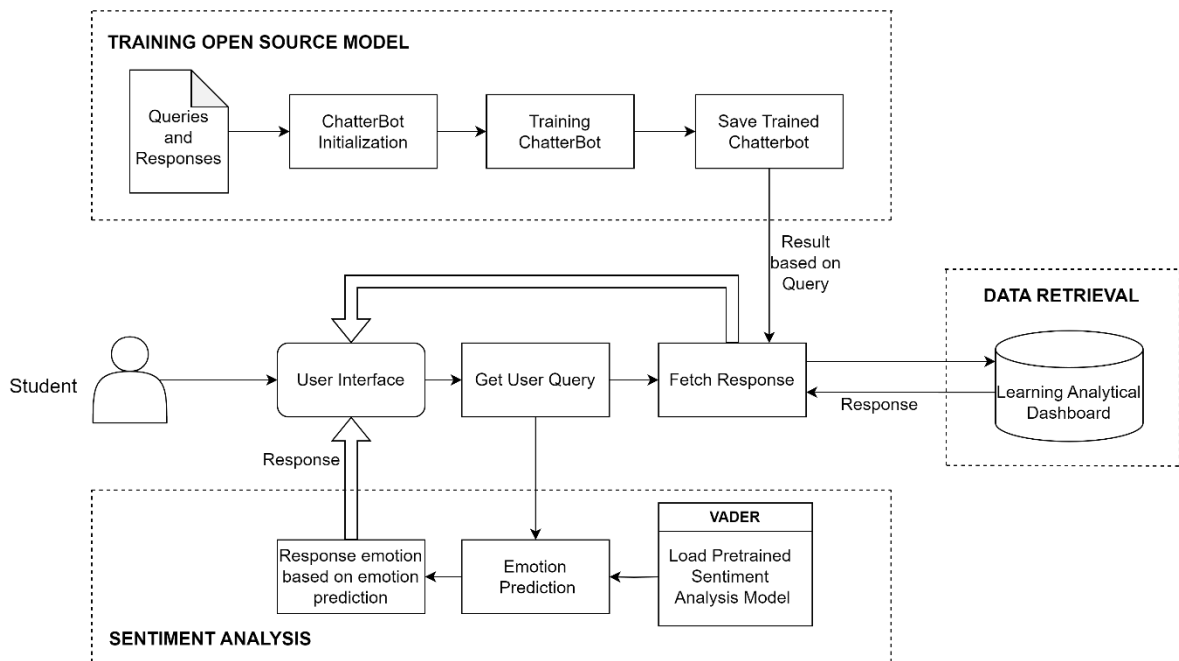


Figure 15: Conceptual Flowchart of a Retrieval-Based model Chat Bot

The next phase will involve training the chatbot using the prepared dataset. During this phase, the ChatterBot framework will process the dataset to understand patterns and relationships between different queries and their corresponding responses. Training will be crucial as it will ensure the chatbot's ability to comprehend and accurately reply to user inputs. Once the training is complete, the trained model will be saved to allow for its deployment without the need for retraining, thereby saving time and computational resources in future sessions.

User interaction with the chatbot will occur through a designated User Interface (UI), which could be a web interface, mobile application, or another platform that will facilitate communication between the user and the chatbot. Upon receiving a user query through the UI, the system will capture this query and fetch an appropriate response from the trained ChatterBot model based on the training data. However, this initial response selection will not yet account for the emotional context of the query.

To incorporate emotional intelligence into the system, the VADER (Valence Aware Dictionary and sEntiment Reasoner) tool will be utilized to analyze the emotional content of the user's input. VADER is a sentiment analysis tool that evaluates text for positive, negative, and neutral emotions, which will be essential for understanding the emotional tone behind the user's query. Based on this emotion prediction, the system will then modify the initial response to better align with the detected emotional state of the user, ensuring that the chatbot's reply is not only contextually accurate but also emotionally sensitive.

Finally, all interactions, including user queries, system responses, and emotion predictions, will be logged and analyzed through a Learning Analytical Dashboard. This dashboard will provide critical insights into the chatbot's performance, user satisfaction, and areas requiring improvement. It will serve as a vital tool for the ongoing refinement of the chatbot system, enabling continuous learning and adaptation. Overall, this methodology will represent a significant advancement in developing intelligent conversational agents, offering both accurate and emotionally aware responses to enhance user satisfaction.

4.2 Training method

The figure 16 details a comprehensive "Plan of Implementation" for training a ChatterBot, which is a type of AI conversational agent. It demonstrates how the system learns from user interactions by organizing this information in a graph format within a database. This method enhances the ChatterBot's ability to recall and respond to user inputs by outlining possible conversation paths based on prior exchanges.

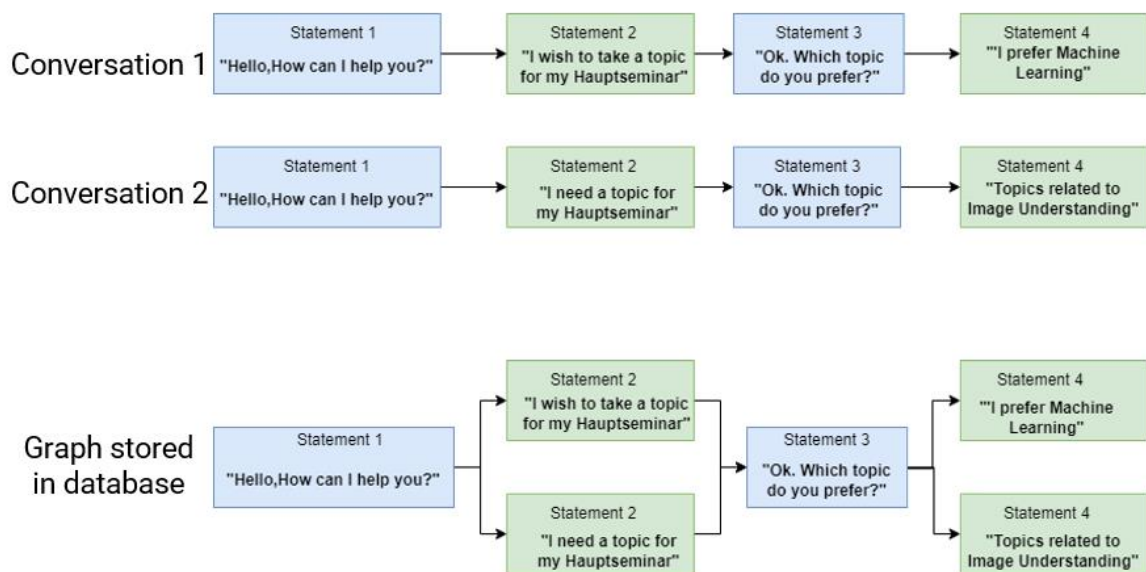


Figure 16: Training process of a ChatterBot [97]

The figure 16 includes two example conversations to illustrate how the ChatterBot processes and retains information. In the first conversation, the bot starts with a typical greeting: "Hello, how can I help you?" The user replies with a specific request: "I wish to take a topic for my Hauptseminar." The bot then seeks clarification: "Ok. Which topic do you prefer?" The user indicates a choice: "I prefer Machine Learning." The second

conversation follows a similar pattern, beginning with the bot's greeting: "Hello, how can I help you?" However, the user's request is slightly altered: "I need a topic for my Hauptseminar." The bot responds with the same follow-up question: "Ok. Which topic do you prefer?" This time, the user expresses a different preference: "Topics related to Image Understanding."

These dialogues are represented in a graph format, illustrating how they are stored in the ChatterBot's database. The graph begins with the common initial greeting ("Hello, how can I help you?"), which then branches into two distinct user responses. Each response leads to the same subsequent bot question ("Ok. Which topic do you prefer?"), followed by two different user preferences. This graph structure emphasizes the bot's ability to distinguish between similar yet unique queries while managing multiple user inputs to provide coherent replies.

The stored graph enables the ChatterBot to anticipate user inquiries based on earlier interactions. For example, when a new user begins with the initial greeting, the bot can reference the stored conversation graph to offer relevant prompts or suggestions. As more interactions are recorded, the system becomes increasingly adept at handling a broader range of user inputs. This method of storing conversations allows the bot to deliver dynamic and contextually relevant responses, enhancing the user experience over time.

Additionally, this graph-based strategy is crucial for the bot's capability to manage complex and varied user requests. In practical applications, such as academic advising or customer service, the bot must navigate nuanced questions and provide personalized guidance. The structured storage of data in the form of a conversation graph ensures that the bot can recall past interactions and use them to inform future responses, resulting in a system that is both adaptive and flexible.

In summary, the figure underscores the importance of structured data storage and learning in AI-driven conversational agents. By capturing and organizing conversation flows as graphs, a ChatterBot can enhance its performance over time, delivering more accurate and contextually relevant responses. This design is vital for creating intelligent and responsive AI systems capable of effectively addressing a wide range of user inquiries.

5 Implementation

This section defines the different methods that were used for building the student assistance system proposed in this study.

5.1 Tools used

In this study, Python was used as the programming language for implementing various aspects of the project. It was chosen for its versatility and extensive libraries suited for web application development, data analysis, and machine learning tasks. Flask, a lightweight web framework in Python, was utilized to build the web application interface. This framework enabled the creation of interactive features that users could easily navigate to interact with the chatbot system. For training and testing the chatbot's conversational abilities, Anaconda provided a robust environment. Anaconda is a platform designed to streamline the management and deployment of Python libraries, ensuring compatibility and enhancing usability during software development. Visual Studio Code was used as the integrated development environment (IDE) for coding and debugging. Its user-friendly interface and efficient editing tools facilitated smooth development and quick iteration of the project components. Together, these tools formed the backbone of the project's technical infrastructure, enabling the team to implement a functional and responsive chatbot system. Python's flexibility allowed for integration of different functionalities, from web interface design to natural language processing capabilities. Flask provided the necessary framework for creating a user-friendly front-end experience, while Anaconda ensured the reliability and efficiency of the machine learning algorithms powering the chatbot's responses. VS Code, as the IDE, supported the development workflow by providing essential tools for writing code and ultimately contributing to the successful deployment of the project.

5.2 Dataset Creation

To build the dataset for the ChatterBot, a manual approach was employed where data entries were curated and structured into a YAML file format. This method ensured simplicity and ease of management throughout the dataset creation process. Each entry in the dataset followed a predefined structure for clarity and consistency. The dataset primarily consisted of two main sections: categories and conversations. Under the 'categories' section, the dataset was classified broadly under a single category such as 'conversations', indicating the general theme of the data contained within. Within the 'conversations' section, individual dialogues were formatted as nested lists. Each dialogue pair comprised two sequential entries: the user query followed by the

corresponding response provided by the chatbot. One difficulty encountered was the time required for creating the dataset manually, ensuring each entry was accurate and useful. This format facilitated straightforward access and retrieval of conversational pairs during the chatbot's training and operational phases.

```
1 categories:
2   - conversations
3
4 conversations:
5   |
6   - "What strategies can I use to ensure my research topic fits within the timeframe of my degree program?"
7   - "To ensure your research topic fits within the timeframe, choose a focused topic, clearly define your research objectives, plan your research activities meticulously, and set realistic deadlines for each phase of"
8   - "How can I make sure my thesis topic doesn't take forever?"
9   - "To ensure your research topic fits within the timeframe, choose a focused topic, clearly define your research objectives, plan your research activities meticulously, and set realistic deadlines for each phase of"
10  - "Tips for picking a doable research project?"
11  - "To ensure your research topic fits within the timeframe, choose a focused topic, clearly define your research objectives, plan your research activities meticulously, and set realistic deadlines for each phase of"
12  - "How do I avoid time traps when choosing a thesis subject?"
13  - "To ensure your research topic fits within the timeframe, choose a focused topic, clearly define your research objectives, plan your research activities meticulously, and set realistic deadlines for each phase of"
14  - "How can I match my research idea to my program's timeline?"
15  - "To ensure your research topic fits within the timeframe, choose a focused topic, clearly define your research objectives, plan your research activities meticulously, and set realistic deadlines for each phase of"
16
17
18  - "How can I adjust my research topic if I find it's too broad or complex?"
19  - "If your research topic is too broad or complex, narrow it down by focusing on a specific aspect or component of the topic, limiting the geographical or demographic scope, or reducing the number of research quest"
20  - "Help! My thesis topic is too big. What now?"
21  - "If your research topic is too broad or complex, narrow it down by focusing on a specific aspect or component of the topic, limiting the geographical or demographic scope, or reducing the number of research quest"
22  - "How can I trim down an oversized research project?"
23  - "If your research topic is too broad or complex, narrow it down by focusing on a specific aspect or component of the topic, limiting the geographical or demographic scope, or reducing the number of research quest"
24  - "When your study bites off more than you can chew?"
25  - "If your research topic is too broad or complex, narrow it down by focusing on a specific aspect or component of the topic, limiting the geographical or demographic scope, or reducing the number of research quest"
26  - "Simplifying a complex thesis topic?"
27  - "If your research topic is too broad or complex, narrow it down by focusing on a specific aspect or component of the topic, limiting the geographical or demographic scope, or reducing the number of research quest"
28
29
30  - "What role does advisor feedback play in managing the scope of a research topic?"
31  - "Advisor feedback is crucial in managing the scope of a research topic as it provides expert insights into the feasibility of the topic, helps refine the research questions, and ensures the study can be completed"
32  - "How can my professor help me keep my thesis on track?"
33  - "Advisor feedback is crucial in managing the scope of a research topic as it provides expert insights into the feasibility of the topic, helps refine the research questions, and ensures the study can be completed"
34  - "Can I use a supervisor's input to shape my research?"
35  - "Advisor feedback is crucial in managing the scope of a research topic as it provides expert insights into the feasibility of the topic, helps refine the research questions, and ensures the study can be completed"
36  - "Why should I listen to my advisor about project size?"
37  - "Advisor feedback is crucial in managing the scope of a research topic as it provides expert insights into the feasibility of the topic, helps refine the research questions, and ensures the study can be completed"
38  - "How can get help to focus your study?"
39  - "Advisor feedback is crucial in managing the scope of a research topic as it provides expert insights into the feasibility of the topic, helps refine the research questions, and ensures the study can be completed"
40
```

Figure 17: Dataset format in YAML used for chatbot training

In figure 17, the format of the dataset is shown, showcasing a structured arrangement of conversational data.

5.3 Training The Chatterbot

A Chatterbot is a conversational agent designed to simulate human-like conversation through natural language processing techniques. It functions as a chatbot framework that enables developers to create interactive chat interfaces for various applications, including customer service, education, and entertainment. The primary purpose of a Chatterbot is to engage users in meaningful dialogue, responding to their queries and providing relevant information based on predefined rules or machine learning algorithms. In this study, the Python ChatterBot module was utilized to implement a conversational interface for the web application. The ChatterBot module in Python is a powerful tool that facilitates the creation of chatbots capable of engaging in natural language conversations. It combines natural language processing methods with machine learning algorithms to generate answers based on user inputs. The decision to use the ChatterBot module was driven by its simplicity and flexibility in building

chatbot functionalities without extensive programming knowledge [57]. It allowed for the customization of responses and the training of the chatbot using a variety of datasets or predefined rules, depending on the specific requirements of the application.

The implementation process began by installing the necessary dependencies for the ChatterBot module using the pip install ChatterBot command. This step ensured that all required libraries were readily available for use within the Python environment. Once installed, ChatterBot was ready to be utilized for creating a chatbot capable of engaging in natural language conversations. Initially, the chatbot started with no prior knowledge of how to communicate. As users interacted with it by entering statements, ChatterBot learned from these interactions. It saved both the user's input and its responses, gradually building a database of knowledge. With each new input, the chatbot improved its ability to generate accurate and contextually relevant responses. To train the chatbot, the ChatterBot module was imported, and a ChatBot instance was created with a specified name, 'Chatting Bot'. Training involved using both custom data from a designated folder and predefined English language corpora available within the ChatterBot library. This training process aimed to enhance the chatbot's conversational abilities by exposing it to diverse patterns and responses commonly encountered in conversations. During implementation, a challenge arose regarding compatibility issues with different Python versions. To resolve this, an alternate Python environment provided by Anaconda was used, ensuring compatibility with the specific version required by ChatterBot. This adjustment allowed the implementation to proceed smoothly without interruptions, ensuring the chatbot could operate effectively within its intended environment.

This sets up and trains a chatbot using the ChatterBot library, which is a machine learning-based conversational dialog engine. This begins by importing the necessary modules, including the core ChatterBot class and a response selection method. Additionally, it imports the logging, system, and OS modules, along with the datetime module for potential time-related functionalities. These imports are crucial for configuring the environment and providing additional functionality to the chatbot. Logging is configured to provide information-level outputs, which will help track the bot's training process. Logging is essential for debugging and monitoring the training procedure, ensuring that any issues or important events are recorded. Next, a ChatBot instance named 'Chatting Bot' is created. This instance is configured to use a specific trainer from ChatterBot, specifically the ChatterBotCorpusTrainer, which is designed to train the bot with pre-existing conversational datasets. The use of

ChatterBotCorpusTrainer is significant because it leverages structured datasets to teach the bot various conversational nuances.

The training process involves two main parts. First, if a specific data folder is provided, the bot will be trained using the data contained within that folder. This allows for custom training with user-specified datasets, which can be particularly useful for domain-specific knowledge or customized conversational patterns. Custom training data ensures that the bot can handle specific topics or jargon that are relevant to the user's needs, making the bot more effective in specialized applications. Second, the bot is trained using the default English corpus provided by ChatterBot, which includes a wide variety of conversational data across different contexts and topics. This corpus training ensures that the bot has a broad understanding of typical conversational structures and can respond appropriately to a wide range of inputs. The standard English corpus covers common phrases, greetings, and responses, enabling the bot to engage in everyday conversations effectively. The training function is executed with specified parameters, kicking off the process of training the chatbot with both custom data and the standard English corpus. This dual approach ensures that the bot is well-rounded, capable of engaging in both general and specialized conversations, making it suitable for applications in study aids, dissertation creation, or other academic and professional uses. By incorporating both custom and general training data, the chatbot becomes versatile and robust, capable of providing accurate and contextually relevant responses across various scenarios. This comprehensive training process is crucial for developing a chatbot that can assist users in a wide range of tasks, from casual interactions to complex, domain-specific queries.

5.4 Testing The Chatterbot

Evaluating the capabilities of the ChatterBot in real-world scenarios, thorough testing was conducted to assess its responsiveness and effectiveness in engaging users through simulated conversations. The testing phase utilized essential libraries such as ChatterBot for creating the chatbot instance, `get_random_response` for selecting responses randomly, and `logging` for managing error levels during execution. Initially, the existence of the database containing the chatbot's knowledge was verified. If the database was not found at the specified location, an error message was generated, indicating the chatbot's temporary unavailability until the issue was resolved. This initial check ensured that interactions with the chatbot proceeded smoothly only when its knowledge base was accessible. During testing, the chatbot instance named 'Chatting Bot' was configured with several logic adapters to enhance its response capabilities.

These adapters included BestMatch for identifying the most suitable response based on the input received, SpecificResponseAdapter for predefined responses to specific queries like 'Help me!', and LowConfidenceAdapter to handle responses when the chatbot's confidence in its answer was below a certain threshold. These configurations aimed to provide varied and contextually appropriate responses tailored to users' inputs. Throughout the testing process, inputs were provided to the chatbot to simulate user interaction. The chatbot processed each message using its trained knowledge and selected an appropriate response based on the context and content of the input.

This is designed to test a trained chatbot using the ChatterBot library. It defines a function for generating responses from the chatbot and an interactive loop for continuous user interaction with the bot. This begins by defining a function named botreply that takes two parameters: messagein (the input message from the user) and db_location (the path to the database where the chatbot's training data is stored, with a default value of "db.sqlite3"). This function is responsible for generating a response from the chatbot based on the input message. The first step within the function is to check if the specified database file exists at the given location. If the database does not exist, an error message is constructed and printed, indicating that the model is not available. This error message includes the current timestamp for logging purposes. In such cases, the function returns a default apology message indicating that the bot is currently unavailable.

If the database file is found, the logging level for ChatterBot is set to WARNING to suppress less critical logs, ensuring that only important messages are displayed. Next, a ChatBot instance named 'Chatting Bot' is created. This instance is configured with several logic adapters, which define how the bot will generate responses. The BestMatch Adapter selects the best response from the bot's training data based on similarity to the input message. The SpecificResponseAdapter provides a specific response to a particular input text. In this case, if the user says, "Help me!", the bot will respond with "mail your query here." The LowConfidenceAdapter handles cases where the bot is not confident in its response. If the confidence level is below a specified threshold (0.65), the bot will respond with "I am sorry, but I do not understand."

The response_selection_method is set to get_random_response, which selects a random response from the possible responses when there are multiple equally suitable options. The read_only parameter is set to True, meaning the bot will not learn from the conversations during this session. Within the function, the input message is processed to generate a reply using the chatbot's get_response method. The response

is converted to a string and printed along with the user's input for easy comparison. Finally, the response is returned. Then enters an infinite loop, allowing continuous interaction with the chatbot. The user is prompted to input a message, and if the input is "bye" (ignoring case and surrounding whitespace), the loop breaks, and the interaction ends. Otherwise, the `botreply` function is called with the user's message, and the bot's response is printed. This interactive loop ensures that the user can have an ongoing conversation with the chatbot, testing its ability to generate appropriate responses based on the training data. By providing detailed feedback on each interaction, the script allows for easy evaluation of the chatbot's performance, making it a useful tool for studying and improving conversational AI systems.

5.5 Sentiment Analysis

Emotion responses are crucial in enhancing the effectiveness of chatterbots by making interactions more empathetic and responsive to users' emotional states. When chatbots can detect emotions such as frustration, happiness, or confusion in user prompts, they can tailor their responses, accordingly, leading to more meaningful interactions. This capability helps in providing personalized support, improving user satisfaction, and creating a more engaging experience. For instance, a chatbot recognizing frustration can offer reassurance or redirect the conversation to address the underlying issue, thereby enhancing user retention and satisfaction. Emotion detection also enables chatbots to adapt their tone and language, making interactions feel more natural and empathetic, like human conversations [TUC2]. Integrating emotion responses into chatterbots can contribute to building trust and rapport with users. By recognizing and appropriately responding to users' emotional cues, chatbots can create a feeling of comprehension and empathy. For example, acknowledging happiness while addressing confusion with clarity can significantly enhance the user's perception of the chatbot's effectiveness and reliability. This emotional responsiveness not only improves user engagement but also strengthens the overall user-bot relationship over time. Ultimately, by harnessing emotion detection capabilities, chatterbots can simulate more human-like interactions, catering to diverse emotional states and preferences, thereby enriching the user experience in various applications from customer service to educational support.

In this study, `TextBlob`, a Python library, was employed for processing textual data, particularly for sentiment analysis to enhance the chatbot's capability to detect and respond to emotions conveyed in user queries. `TextBlob` offers a straightforward

API that facilitates various natural language processing tasks essential for understanding and analyzing text. These activities involve tasks such as identifying parts of speech, extracting noun phrases, analyzing sentiment, employing classification methods like Naive Bayes and Decision Tree, tokenizing text into words and sentences, and parsing for syntactic analysis. One of the key features of TextBlob is its sentiment analysis functionality, which assigns a polarity score ranging from -1 (negative sentiment) to +1 (positive sentiment) to input text. This sentiment polarity score indicates the emotional tone conveyed in the text, helping the chatbot determine the user's sentiment. Based on this score, the chatbot maps the sentiment polarity to predefined emotions such as 'Happy' for positive sentiment, 'Sad' for negative sentiment, and 'Neutral' for neutral sentiment. This mapping allows the chatbot to interpret and respond appropriately to the user's emotional state. TextBlob supports noun phrase extraction, which identifies and extracts meaningful noun phrases from text, aiding in understanding the context and subject matter of user queries. Part-of-speech tagging assigns grammatical categories (like noun, verb, adjective) to words in a sentence, enabling the chatbot to analyze the syntactic structure of text and derive meaning from it. Another useful feature is tokenization, which breaks down text into individual words or sentences, essential for further analysis and processing. Additionally, TextBlob provides capabilities for word and phrase frequencies, n-grams (sequences of adjacent words), word inflection (handling pluralization and singularization), lemmatization (reducing words to their base or root form), and spelling correction, ensuring accurate understanding and interpretation of user inputs. TextBlob's extensibility allows for the integration of new models or languages through extensions, enhancing its versatility and applicability across different domains and languages. This flexibility makes TextBlob a valuable tool in building intelligent applications like chatbots that require robust NLP capabilities to interact effectively with users. By using TextBlob for sentiment analysis and other NLP tasks, the chatbot in this study can enhance its responsiveness and adaptability, delivering interactions that are personalized and empathetic with users based on their expressed emotions in text queries. This integration underscores the importance of NLP tools like TextBlob in advancing the capabilities of AI-powered chatbots to understand and respond appropriately to human emotions in natural language interactions.

This is designed to analyse and identify the emotion conveyed in a user's input query. It uses two main functions: `get_emotion` and `detect_emotion`, along with the TextBlob library for sentiment analysis. The `get_emotion` function takes a user query as input and utilizes the TextBlob library to perform sentiment analysis. TextBlob

processes the input query to determine its sentiment polarity, which measures the emotional tone of the text on a scale from -1 to 1. A polarity value greater than 0 indicates a positive sentiment, less than 0 indicates a negative sentiment, and a value of 0 suggests a neutral sentiment.

Based on the sentiment polarity, the function maps the sentiment to a corresponding emotion using a predefined dictionary. If the sentiment polarity is positive, the emotion is classified as 'happy'. If it is negative, the emotion is classified as 'sad'. If the sentiment is neutral, the emotion is classified as 'neutral'. The function then returns the determined emotion. The `detect_emotion` function extends the analysis by identifying specific types of emotions or intents based on keywords within the user's input sentence. It defines three sets of keywords: `surprise_keywords`, `greeting_keywords`, and `goodbye_keywords`, which represent different types of emotions or conversational intents.

The function first converts the input sentence to lowercase to ensure that keyword matching is case-insensitive. It then checks for the presence of keywords related to surprise, greetings, or goodbyes in the input sentence. If any keyword from the `surprise_keywords` set is found, the function prints 'surprise' and returns 'surprise'. If any keyword from the `greeting_keywords` set is present, it prints 'greeting' and returns 'greeting'. If any keyword from the `goodbye_keywords` set is detected, it prints 'goodbye' and returns 'goodbye'. If none of these keywords are found in the sentence, the function calls `get_emotion` to analyse the sentiment of the sentence and return the corresponding emotion ('happy', 'sad', or 'neutral'). This approach provides a dual-layered analysis of the user input: first, by detecting specific conversational intents based on keywords and, second, by analysing the overall sentiment to infer general emotional states. This combination allows the system to handle a wide range of user queries effectively, categorizing them into specific emotional responses or conversational intents.

5.6 Interfacing of Chatterbot and sentimental analysis with web application

Integrating a trained ChatterBot and sentiment analysis system with a Flask-based web application involves developing a Flask app to manage user interactions and process queries through ChatterBot, which generates responses based on input data. Once a response is generated, it undergoes sentiment analysis using tools like. This sentiment is then used to adjust an avatar's animation on the web page, providing a

visual representation of the detected emotion such as a happy, sad, or neutral avatar. The system delivers the response and animated avatar to the user in real-time, ensuring a seamless and engaging interaction. In the implementation of the avatar interaction system within the Flask-based web application, the process is centered around dynamically adjusting avatar animations based on detected emotions. The `processInput` function is designed to handle different emotional states by invoking specific avatar actions. These actions are defined in an object where each emotion, such as "greeting," "surprise," "sad," "happy," "goodbye," and "neutral," has a corresponding function that triggers the appropriate animation for the selected avatar profile. The avatar profile, which is stored in the browser's local storage, determines whether the avatar is "Ada" or "Obi." Depending on this profile, the function calls the relevant animation function, such as `Ada_Happy()` or `Obi_Sad()`, to reflect the current emotional state. This approach ensures that the avatar responds accurately to the emotional context of user interactions, providing a personalized and engaging visual experience. If an unknown emotion is detected, the function logs an error message, ensuring that only recognized emotions trigger specific animations. This enhances user interaction by dynamically adapting the avatar's behavior to match the sentiment of the conversation. The overall approach includes testing for functionality, accuracy, and performance, along with gathering user feedback for ongoing improvements. This creates an interactive, emotionally responsive experience that enhances user engagement through a dynamic Flask-based interface.

A Flask-based chatbot application that integrates conversational capabilities with emotional recognition. The chatbot function handles POST requests to the Flask server, processes user input, detects emotions, and generates responses based on the detected emotions and specific keywords. The function starts by checking if the request method is POST, ensuring that it only processes data sent via POST requests. It retrieves the data from the request, which is initially in byte format, and decodes it to a UTF-8 string. This string is then printed for debugging purposes, and it is converted to a string format for further analysis. The `detect_emotion` function is used to analyze the emotional content of the decoded message. It classifies the sentiment into categories such as surprise, greeting, goodbye, happiness, or sadness. This detected emotion is printed for debugging purposes. Several sets of keywords are defined for recognizing specific types of responses. These keywords include terms related to surprise, goodbyes, happiness, and sadness. The input message is converted to lowercase to facilitate case-insensitive keyword matching.

The function checks for the presence of these keywords in the message. If surprise-related keywords are found, the response is set to "Wow! That sounds incredible!" If goodbye keywords are detected, the response is "Goodbye! Have a great day!" For happiness-related keywords, the response becomes "I'm glad to hear that you're happy! What made your day?" If sadness-related keywords are identified, the response is "I'm sorry to hear that you're feeling sad. Would you like to talk about what's bothering you?" If none of the specific keywords are present, the function defaults to calling the chat_response function, which generates a general response based on the chatbot's training data.

In addition to generating text-based responses, the system is designed to adjust the avatar's appearance based on the detected emotion. If the emotion detected is happiness, the avatar's expression will be happy. Conversely, if the emotion detected is sadness, the avatar will reflect a sad expression. This feature enhances the user experience by providing a visual representation that aligns with the user's emotional state. The function returns a JSON response containing the original user message, the generated response, and the detected emotion. This JSON response is sent back to the client, which could be a web interface or another application component, enabling it to display both the chatbot's response and the appropriate avatar expression to the user. This integration ensures that the chatbot offers a more personalized and engaging experience, aligning both the conversational content and visual elements with the user's emotional state.

5.7 Learning analytics dashboard Integration

The Learning analytic dashboard is an innovative dashboard designed to empower students by providing comprehensive insights into their test and exam performance. This tool allows students to effectively monitor their academic progress and evaluate their performance over time. By presenting data in an intuitive and accessible manner, the Analytic dashboard helps students identify strengths and areas for improvement, set achievable goals, and track their progress toward academic success. With features such as detailed performance metrics, trend analysis, and personalized feedback, this dashboard serves as a vital resource for students seeking to enhance their learning outcomes and achieve their full potential.

The dashboard essentially consists of data representations like Student summary list, Correlation between different tests, Test types based on students' matriculation number in both Teachers and Students view. Graphical representation of students test

information with respect to Search, Presentation, Discussion and Report is stored in the database and the chatbot can essentially leads the student to the database. Figure 18 shows the learning analytics dashboard representation of a student's overall test information.

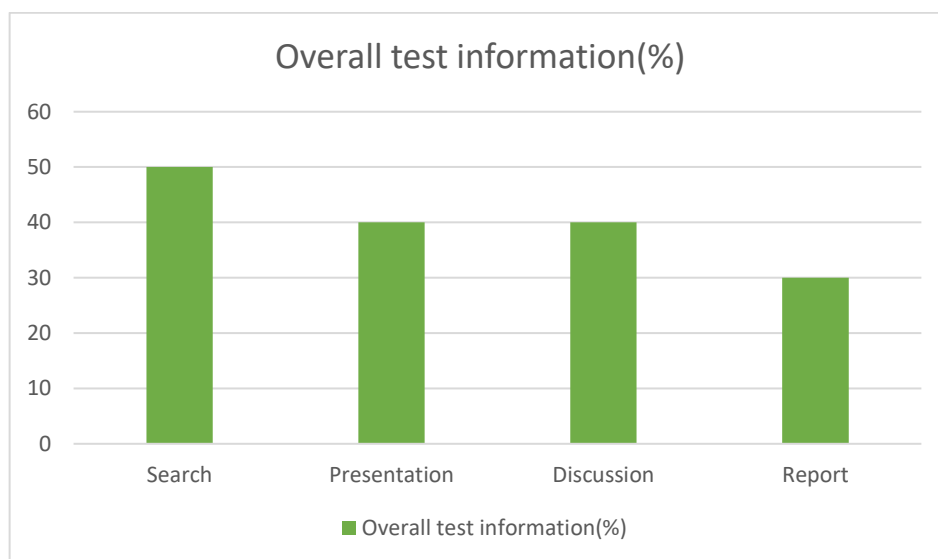


Figure 18: Learning analytics dashboard representation

To combine a learning analytics dashboard with a retrieval-based chatbot, match the chatbot's data retrieval system to the dashboard's analytics capabilities. This includes creating data pipelines to transport user interaction measurements and learning outcomes from the chatbot to the dashboard. Ensure that the dashboard can display these indicators in real time, providing insights into user engagement and learning progress. The chatbot possibly should redirect the student to their respective data in the learning analytics dashboard.

The figure 19 shows the expected view of the front end. The Tutoring chatbot responds either by providing a link which redirects to the dashboard where the student can find their performance. There by interacting with the tutoring bot regarding the possibilities of improvement and feedback.

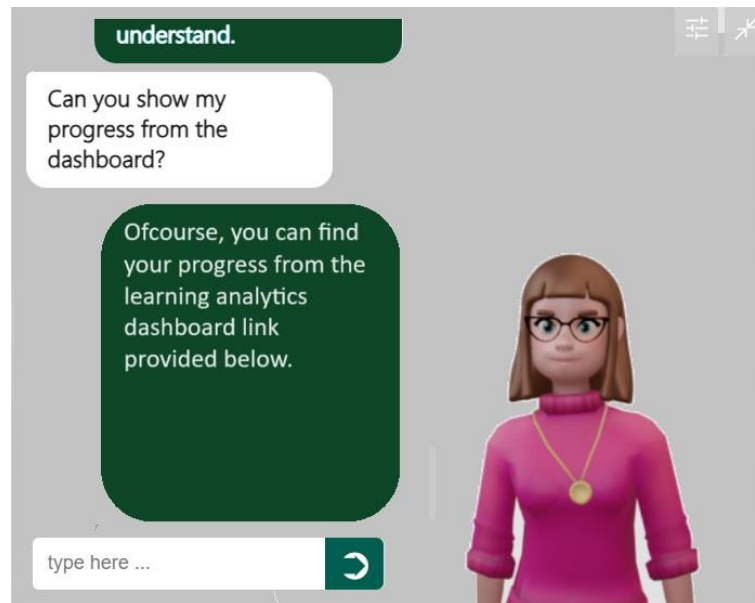


Figure 19: Expected view of the front end

6 Results and Evaluation

The Results chapter provides a thorough assessment of the capabilities and interactions enabled by the Virtual Tutoring chatbot built for this study. The numbers depict many aspects of the chatbot's functioning, such as its capacity to provide academic support, evaluate sentiment, and engage people via a digital avatar. Figure 18 displays the chatbot's ability to provide thorough dissertation research and writing support, with an emphasis on an organized approach and professional advice. Subsequent figures, such as Figures 19–27, show the chatbot's sentiment analysis capabilities and how they are integrated into user interactions, with the BOT responding to various emotional tones and improving the user experience through tailored, empathic responses.

Figure (18), is a conversation with a Virtual Tutoring BOT, showcasing its ability to provide detailed academic support. In the first interaction, the user asks, "How do I conduct research for my dissertation?" The BOT responds with a comprehensive answer: "Research for a dissertation involves gathering relevant literature, collecting data (if applicable), and critically analyzing existing research in your field. Utilize academic databases, libraries, and online resources to find scholarly sources, and consider consulting with experts in your field for guidance." This response highlights the BOT's capability to offer practical advice on conducting thorough research, emphasizing the importance of utilizing various resources and seeking expert input. In the second interaction, the user queries, "How do I write a dissertation?" The BOT's reply provides a structured overview: "Writing a dissertation involves several stages, including selecting a topic, conducting research, drafting chapters, and revising your work. It's essential to follow a structured approach and seek guidance from your academic advisor throughout the process." This explanation outlines the key phases of dissertation writing and underscores the need for a systematic approach and advisor consultation.

```

Ask Bot:How do I conduct research for my dissertation?

YOU (Input): How do I conduct research for my dissertation?
Virtual Tutoring BOT: Research for a dissertation involves gathering relevant literature, collecting data (if applicable), and critically analyzing existing research in your field. Utilize academic databases, libraries, and online resources to find scholarly sources, and consider consulting with experts in your field for guidance.

Ask Bot:How do I write a dissertation?

YOU (Input): How do I write a dissertation?
Virtual Tutoring BOT: Writing a dissertation involves several stages, including selecting a topic, conducting research, drafting chapters, and revising your work. It's essential to follow a structured approach and seek guidance from your academic advisor throughout the process.

```

Figure 20: Chatbot interaction

```

Enter your query: I am Very Happy to See you
The emotion of the user query is: Happy/Excited

```

Figure 21: Emotion detection

The figure 19, shows a sentiment analysis of a user query, specifically analyzing the text: "Enter your query; I am very happy to see you." In this context, the sentiment analysis focuses on determining the emotional tone of the statement. The text expresses a positive sentiment, characterized by the phrase "I am very happy to see you," which conveys a feeling of joy and enthusiasm. The sentiment analysis would likely categorize this statement as having a high positive polarity, indicating a strong sense of happiness and friendliness. This analysis helps in understanding the emotional context of the user's message and tailoring responses or interactions accordingly.

The figure 20, illustrates a key aspect of our study's results, showcasing a digital avatar used in our interactive chatbot system. The avatar, depicted with raised hands, serves as a visual representation of the virtual assistant developed in our study. Gestures are designed to convey a welcoming and professional demeanor. The presence of two speech bubbles, one stating "Hello" and the other "Greetings!", highlights the avatar's role in engaging with users. These greetings are part of the interactive features implemented to enhance user experience by providing friendly and approachable responses. The design and functionality of the avatar, including its animations and responses, were tailored to align with the sentiment analysis results

obtained from user interactions, ensuring that the avatar's expressions and messages accurately reflect the emotional tone of the conversation.

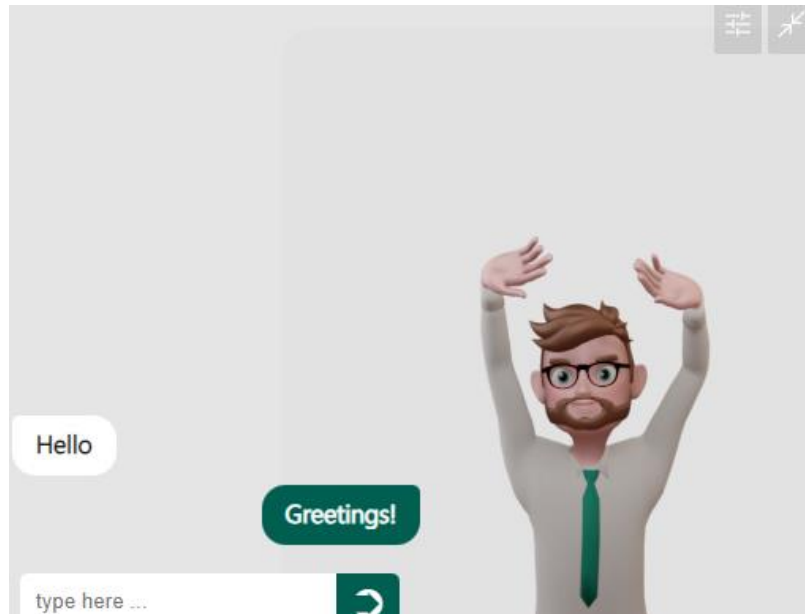


Figure 22: Greetings

The figure 21, depicts a digital conversation between two characters, showcasing a positive interaction facilitated by a virtual assistant or chatbot. In this exchange, the first character, represented by an avatar, expresses a feeling of joy with the statement, "I am very happy today." The second character responds warmly with, "I'm glad to hear that you're happy! What made your day?" This reply not only acknowledges the user's positive emotion but also prompts further engagement by inviting the user to share more about their day. This interaction highlights the chatbot's role in fostering an engaging and supportive conversation. By recognizing and affirming the user's happiness, the system enhances the user experience and encourages a more personalized dialogue.

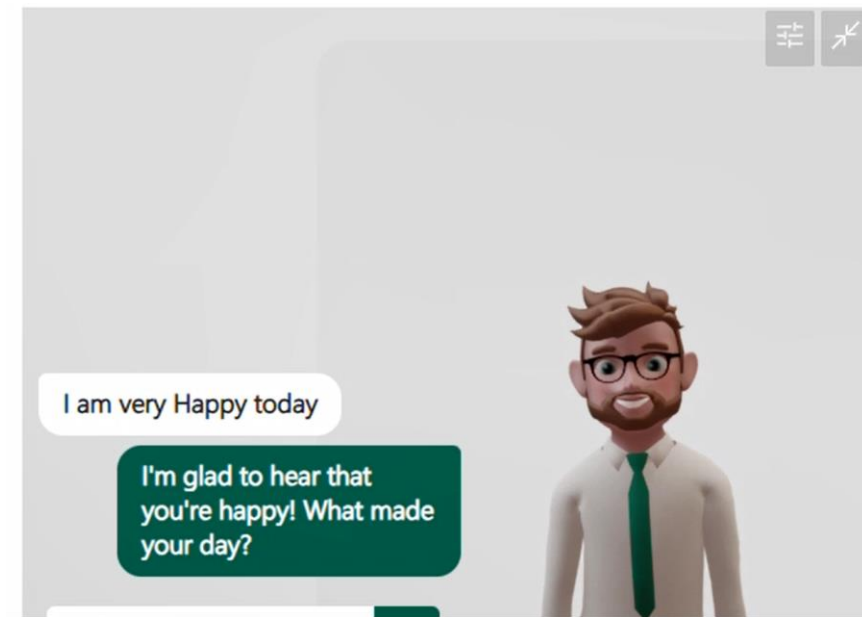


Figure 23: Happy emotion

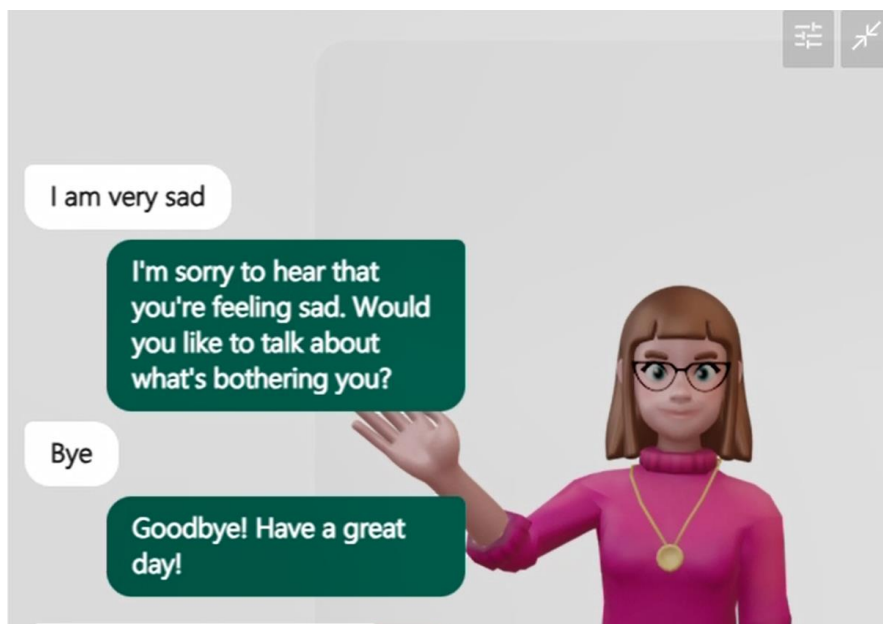


Figure 24: Sad emotion

The figure 22, illustrates a conversational interaction between two entities within our study's system. The first entity expresses a feeling of sadness with the statement, "I am very sad." In response, the second entity, a humanoid figure without facial

features delivers two distinct messages. The first message, "I'm sorry to hear that you're feeling sad. Would you like to talk about what's bothering you?" reflects an empathetic approach, aiming to engage the user in a supportive dialogue. This response is designed to offer comfort and invite further conversation, demonstrating the system's ability to recognize and address emotional states effectively. Following this, the second message, "Bye," is accompanied by a closing remark from the humanoid figure: "Goodbye! Have a great day!" This transition from a supportive message to a farewell shows the system's ability to handle various emotional responses and provide appropriate, context-sensitive interactions. The change in tone from empathetic to a courteous goodbye exemplifies the system's capability to navigate different phases of user interaction gracefully.

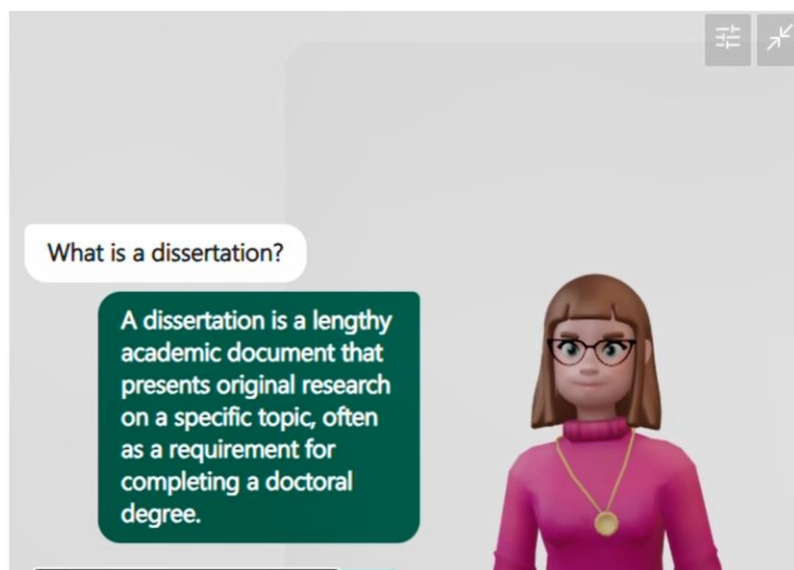


Figure 25: Neutral emotion

The figure 23, shows a digital avatar engaged in an educational interaction with a user. The avatar, exhibiting a neutral emotion, is shown with a speech bubble that inquires, "What is a dissertation?" This neutral tone suggests the avatar's role in providing factual and informative content without conveying any emotional stance. Accompanying the avatar's question is a green text box that provides a detailed answer: "A dissertation is a lengthy academic document that presents original research on a specific topic, often as a requirement for completing a doctoral degree." This explanation serves to clarify the concept of a dissertation, highlighting its role as a substantial academic document essential for doctoral studies.

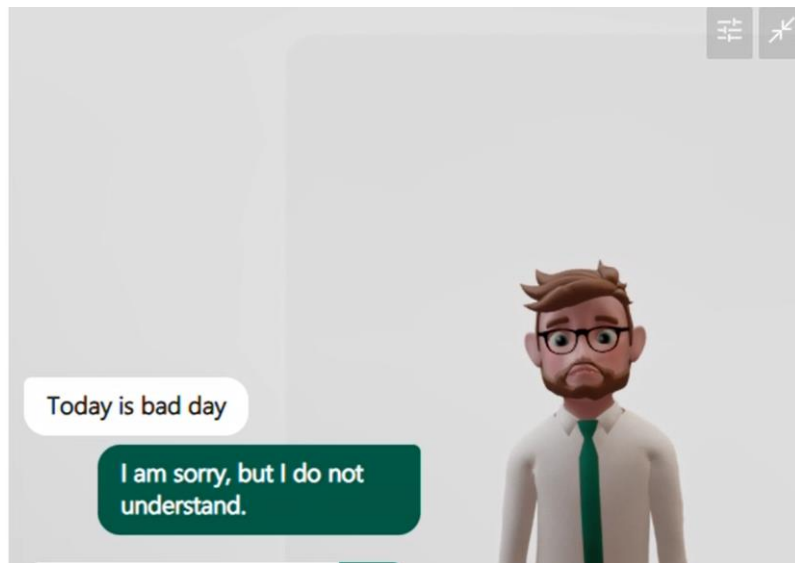


Figure 26: Sad emotion

The figure 24, shows an interaction involving a digital avatar designed to represent a chatbot. The avatar displays a slightly downcast demeanor, indicative of the user's expressed emotion of sadness. The first speech bubble from the user says, "Today is a bad day," reflecting a negative emotional state. The avatar's response in the second speech bubble, "I am sorry, but I do not understand," highlights a limitation in the chatbot's ability to fully comprehend or address the user's emotional statement.

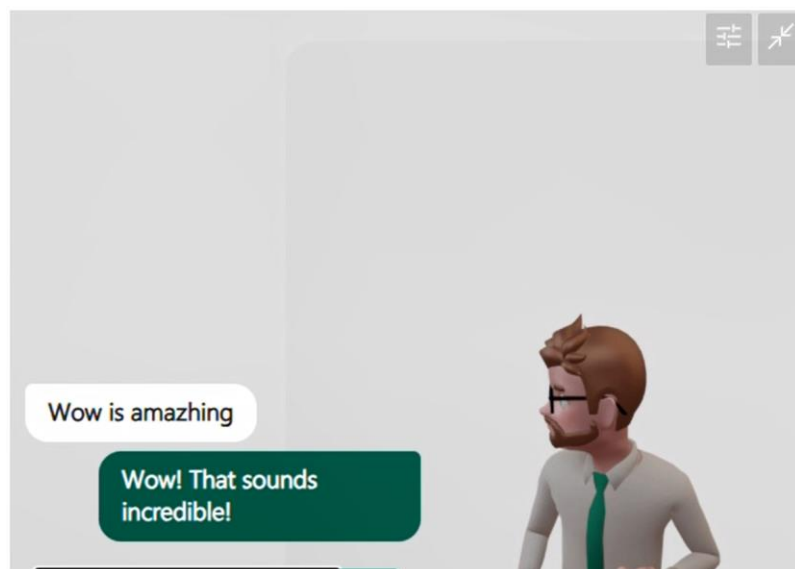


Figure 27: Excitement emotion

The figure 25, represents a moment of excitement conveyed through a digital avatar. The character, shown with an enthusiastic demeanor, engages in a lively exchange through two speech bubbles. The first bubble exclaims, "Wow is amazing," while the second bubble responds with, "Wow! That sounds incredible!" This interaction clearly demonstrates the avatar's positive reaction to excitement. The dialogue highlights the avatar's role in amplifying the sense of enthusiasm and encouragement. By mirroring the user's excitement and expressing awe, the avatar enhances the engagement and emotional impact of the conversation. This type of interaction contributes to a more engaging and interactive user experience.

Due resource limitation, the analytics dashboard is not available because of which the chatbot front end is integrated to a normal interface to demonstrate the result.

6.1 Technical Evaluation

In this study, the primary objectives were methodically addressed to develop a robust interactive system. Firstly, the dataset was prepared for training the ChatterBot, ensuring it was well-suited to support conversational scenarios. The ChatterBot was then trained using this dataset, allowing it to generate relevant and contextually appropriate responses. Following the training phase, the ChatterBot undergoes rigorous testing to validate its accuracy and reliability in handling various queries. Concurrently, sentiment analysis was implemented using TextBlob to assess the emotional tone of user inputs. This analysis provided a foundation for tailoring the chatbot's responses based on the detected sentiment. Finally, the ChatterBot and sentiment analysis were integrated into a web application, creating a seamless chat interface where users could interact with the chatbot and receive responses that reflected their emotional context. This integration ensured that the system not only responded accurately but also engaged users in a meaningful and emotionally aware manner.

The studies on chatbot technology, particularly in educational settings, highlight several advancements and challenges. For instance, the study by [17] pointed out that the effectiveness of chatbots largely depends on the quality of the input data and emphasized the need for human oversight to ensure accuracy. This study approach incorporates a rigorous dataset preparation and training phase, ensuring that the ChatterBot's responses are accurate and reliable, which addresses the data quality concerns highlighted in [17]. The study by [18] focused on Intelligent Tutoring Systems (ITS) and their impact on various educational fields, noting that while ITS can significantly enhance student achievement, their scope might be limited by database

coverage. The integration of sentiment analysis into a web application also improves user interaction, making the system more responsive and effective in educational contexts, thus addressing the integration and ethical challenges discussed in [18]. The study by, [19] examined chatbot technology from historical, technological, and conceptual perspectives, identifying a rapid increase in chatbot capabilities but also underscoring the limitation of chatbots in understanding and expressing empathy. By integrating advanced sentiment analysis using TextBlob with the ChatterBot, this study enhances the chatbot's ability to respond appropriately based on the user's emotional state. This innovation directly tackles the issue of chatbots lacking empathy, as noted in [19].

6.2 Performance Assessment

The chatbot developed for this study is trained on a dataset used specifically to the intended application, which introduces a limitation regarding its generalizability. Because the training data is customized to suit particular use cases, the chatbot may struggle to provide accurate responses to queries outside of its training scope. This specificity can result in incorrect or less relevant answers when faced with unfamiliar topics or questions that deviate from the dataset's content. While this focused training enhances the chatbot's performance within its designed context, it also highlights a potential shortcoming in handling a broader range of inquiries. Consequently, this limitation necessitates continuous updating and expansion of the training dataset to improve the chatbot's adaptability and accuracy across diverse subjects.

The sentiment analysis implemented in this study relies on a pre-trained model and a set of predefined keywords to identify emotions. While effective for detecting basic sentiments such as happy, sad, and neutral, this approach may fall short in accurately capturing and interpreting more nuanced emotional states. The reliance on a limited set of emotional categories restricts the chatbot's ability to handle complex or subtle emotional expressions. This constraint can reduce the efficiency of sentiment analysis, as it may not fully address the diverse spectrum of human emotions that users might convey. To overcome this limitation, future improvements could involve incorporating more advanced sentiment analysis models capable of recognizing a broader range of emotional nuances, thereby enhancing the chatbot's responsiveness to varied emotional contexts.

7 Conclusion

This study involved developing a chatbot system with a digital avatar capable of interacting with users based on their emotional expressions. The system utilized sentiment analysis to assess the emotional tone of user inputs and adjust the avatar's responses and animations accordingly. The core of the chatbot functionality was implemented using the ChatterBot library, which facilitated the generation of responses based on user queries. ChatterBot is a Python library designed to create conversational chatbots, capable of learning from interactions and generating contextually relevant replies. The sentiment analysis component, powered by TextBlob, was used to evaluate the emotional tone of these responses. TextBlob is a text-processing library that accesses common natural language processing tasks, including sentiment analysis. The polarity score generated by TextBlob helped determine whether the sentiment of the response was positive, negative, or neutral. An essential aspect of the system was the avatar's ability to visually represent different emotions. Using JavaScript, developed functions to handle various emotional states detected by the sentiment analysis. For instance, positive sentiments triggered happy or enthusiastic animations, while negative sentiments prompted sad or sympathetic responses. This dynamic visual feedback was aimed at enhancing user interaction by providing a more engaging and emotionally responsive experience. The implementation included a user interface where users could input their queries and receive responses from the chatbot. The avatar's reactions, including animations and responses, were developed to reflect the sentiment of the user's input. This interface was built using Flask for the backend, allowing seamless integration of the chatbot and avatar system into a web application. The avatar's behavior was designed to respond to various emotional cues, including greetings, surprises, sadness, happiness, and neutrality.

The integration of sentiment analysis allowed the chatbot to respond more appropriately to the emotional tone of user inputs. For example, when a user expressed happiness, the avatar's enthusiastic response and animations reinforced the positive interaction, leading to increased user satisfaction. Conversely, when users expressed sadness, the avatar's sympathetic response aimed to provide comfort and support. The system demonstrated its capability to adapt in real-time based on the sentiment analysis results. This adaptability was evident in the avatar's ability to change its animations and responses dynamically, reflecting the user's emotional state accurately. For instance, the avatar's transition from a neutral stance to a happy or sad

animation effectively mirrored the user's expressed emotions, enhancing the conversational experience. The chatbot's ability to handle both casual and informational queries was tested. For example, when users asked about conducting or writing a dissertation, the chatbot provided detailed and structured answers, showcasing its effectiveness as an educational tool. The avatar's neutral demeanor in these interactions was appropriate, aligning with the informational nature of the responses. By incorporating sentiment analysis, chatbots can offer more emotionally intelligent interactions, aligning their responses with the user's emotional state. This capability can significantly improve user satisfaction and engagement, making virtual assistants more effective in both casual and professional contexts. As the final integration of this study, it is necessary to integrate an analytic dashboard with the developed chatbot interface. However, the analytic dashboard is not available at the moment. If the dashboard is provided, it can be integrated with the chatbot.

For future enhancements, incorporating a generative chatbot could significantly improve the effectiveness of user interactions. Unlike rule-based systems that generate responses based on predefined patterns and datasets, a generative chatbot uses advanced machine learning techniques to create responses dynamically. This capability allows the chatbot to produce more natural, contextually relevant, and diverse interactions. The chatbot can engage in more fluid and adaptive conversations, enhancing user experience and satisfaction. The generative approach would not only provide more engaging responses but also enable the chatbot to handle a wider range of topics and queries, making it a more versatile tool in various applications, from customer support to educational tutoring.

Another key area for future enhancement involves improving sentiment prediction accuracy. Currently, the system relies on a pre-trained sentiment analysis model, which may have limitations in capturing the full spectrum of emotional expressions. By developing and training a custom sentiment analysis model, this can use the model to better recognize and interpret a wider array of emotional nuances specific to this application. This approach would involve collecting and annotating a more comprehensive dataset of emotional expressions and using advanced machine learning techniques to refine the model's accuracy. Enhanced sentiment prediction capabilities would allow the chatbot to respond more precisely to users' emotional states, leading to more empathetic and contextually appropriate interactions.

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