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Student Registration Chatbot: A Large Language Model Approach - A Case Study of Adekunle Ajasin University Akungba Akoko, Nigeria

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ABSTRACT

Many educational institutions struggle with inefficient student registration processes, often involving manual intervention due to issues like long waiting time, burden of repetitive registration, forgotten passwords or login difficulties. The study aims to refine the registration processes at Adekunle Ajasin University by developing an automated student registration chatbot. Using large language model (LLM) and prompt engineering technique, the bot simplifies the registration processes and eliminates the over-reliance and direct dependent on administrative support. The student registration bot, built with JavaScript and Next.js framework, interacts with the OpenAI GPT-3.5 model and leverages Retrieval-Augmented Generation (RAG) with a Pinecone database to retrieve relevant information for responses. Also, the Postman facilitates the translation of students' text queries into structured queries for database interactions with the backend. The waiting time and waiting costs of five major parameters were used as our performance metrics. These are login issues, password reset, fee payment status, result visibility and course registration errors. Comparative analysis is done with the existing model. Experimental results demonstrate that the bot's waiting time and costs have a better performance over the existing model on all the metrics thereby leading to improved administrative efficiency and better student experience.

Keywords: Generative Pretrained Model, Retrieval-Augmented Generation, Pinecone Database, Postman and Prompt Engineering.

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1. INTRODUCTION

Student registration process in higher institution of learning is a crucial administrative process that serves multiple interconnected purposes for both the student and the institution. However, the issues of long waiting times, the burden of repetitive registration issues and over-reliance on Information and Communication Technology (ICT) staff in Adekunle Ajasin University, Akungba-Akoko (AAUA) need to be addressed. This concern undermines the student experience, morale and academic performance. As technology increases, taking away some mundane tasks become more necessary to leverage automation and improve the efficiency of administrative operations. To address this, most scholars use the chatbot system. In (Lalwani et al., 2018 ; Pinxteren et al., 2020), The authors define Chatbot system as a computer program designed to simulate conversation with human users, typically through text, speech, facial expression and gestures. According to the authors, it consists of three categories: chatbots without embodiment, chatbots with embodiment and physically embodied robots.

Heryandi, (2020) proposes a chatbot solution to simplify academic record monitoring for students and parents at higher education institutions using a Telegram chatbot to provide easy access to information like attendance, grades, and financial records unlike web-based systems that require complex authentication processes, especially for parents. Also, Algabri et al., (2023) explores chatbots to enhance personalized learning that adapt its teaching strategies to meet individual needs. Modran et al., (2025) developed an intelligent chatbot tutoring system to enhance university student learning. Their system combines Retrieval-Augmented Generation (RAG) with a custom Large Language Model (LLM), specifically addressing the limitations of traditional tutoring and the accuracy issues of using generic LLMs like ChatGPT for course-specific help.

While the authors have contributed to the body of knowledge, certain challenges are still observed especially in AAUA. Among these are:

- Delays that disproportionately impact underserved students. Despite the availability of web-based student portals system currently in use in AAUA.
- Unable to fully exploit the Retrieval-Augmented Generation (RAG), making them unable to reason over institution-specific, frequently updated documents such as fee schedules, course correction procedures or portal usage guidelines. Consequently, students experience long queues, delayed issue resolution and inconsistent information, especially during peak registration periods.

The remainder of this paper is organized as follows. Section II discusses the related work. Section III is on Methodology. In Section IV, we present our results and discussions. We provide a conclusion in Section V.

2. RELATED WORKS

Many works have been done in the area of students' registration,. For example, Wang et al., (2024) discusses the exciting potential of large language models (LLMs) in education. The paper surveys how LLMs can be used in various educational settings, including helping students and teachers, personalizing learning experiences, and through commercially available tools.

Heryandi, (2020) proposes a chatbot solution to simplify academic record monitoring for students and parents at higher education institutions using a Telegram chatbot to provide easy access to information like attendance, grades and financial records unlike web-based systems that require complex authentication processes, especially for parents. By leveraging Telegram's API, the chatbot can deliver information directly to users through a familiar and user-friendly platform. Algabri et al., (2023) explores the potential of using artificial intelligence, particularly chatbots, to enhance personalized learning. The study aims to develop an emotionally realistic chatbot that can provide tailored educational support to students. By analyzing student performance and feedback, the chatbot can adapt its teaching strategies to meet individual needs. This approach can potentially reduce the costs of informal education and improve student engagement and learning outcomes. Modran et al., (2025) describes the development of an intelligent chatbot tutoring system designed to improve university student learning. They addressed the problem of traditional tutoring that has limitations (availability, quality, scalability), and using generic LLMs like ChatGPT alone can lead to inaccurate or non-course-specific help.

The researchers propose a system that combines Retrieval Augmented Generation (RAG) with a custom Large Language Model (LLM). Modran et al., (2024) discusses the development of a specialized GPT model designed to assist students in programming education to proffer solutions to the general-purpose language models that are not optimal for the specific challenges of programming education. They used OpenAI GPT-4 model, named CVTC Coding Expert, able to generate programming code, debug code and improve code. To interact with Open AI mode, the OpenAI API library for Javascript was used. A web application was developed for interacting with GPT model created using HTMLS, CSS3 and Javascript. Kang et al., (2024) describes the development of a chatbot called "School Guardian Angel" to prevent violence among elementary school students. The chatbot was designed using KakaoTalk and evaluated through a formative study with fifth and sixth-grade students. The results show that the chatbot is accessible and useful for students. However, further research is needed to assess its effectiveness with a wider range of age groups.

We appreciate the work of these authors, especially Heryandi (2020), Mordan et al., (2024) and Mordan et al., (2025) for giving us the insight to add value to the body of knowledge. However, the shortcomings observed have made it possible for us to make our contribution, for example, in Heryandi (2020), the issue tightly coupled with registration workflows, fee payment procedures or institutional were not addressed, Also in Mordan et al., (2024), the author rarely integrate vector databases such as Pinecone into operational university portals, nor do they explicitly model registration-specific problems like fee payment anomalies, course correction, and portal access recovery. Furthermore, the RAG-based tutoring system proposed by Mordan et al., (2025) was designed for course content not administrative processes. Our work is differentiated from these work by:

- Fully exploiting the Retrieval-Augmented Generation (RAG), to develop our automated student registration chatbot.
- Addressing the issue of Delays that disproportionately impact underserved students. Despite the availability of web-based student portals system currently in use in AAUA.
- Formulating a solution-based system to determine our automated student registration chatbot waiting costs.
  This to the best of our knowledge is yet to appear in literature.

3. PROPOSED METHODOLOGY

The proposed system consists of two main modules: (i) the User Query Engine, which handles user interaction, retrieval and prompt construction; (ii) the GPT Model Engine, which generates responses based on both the user query and retrieved institutional knowledge.as shown in Figure 1. The User Query Engine is implemented as a Next.js API route running on Node.js. it goes through the Tokenization and Pre-processing, Query Embedding, Vector Retrieval and Prompt Construction. The Tokenization and Pre-processing take the raw user message and normalized it (lower-casing, removal of extra whitespace, basic spelling normalization where possible) while preserving semantic content. The Query Embedding: convert the normalized text into text-embedding-endpoint to obtain a dimensional query vector.

Vector Retrieval allows the query embedding to be converted to Pinecone, which returns the top-k (typically k = 5) most similar knowledge chunks using cosine similarity. The Prompt Construction uses the retrieved chunks and concatenated into a structured context section, followed by the user's original query. We include explicit system-level instructions to answer strictly according to AAUA registration policies and the provided context and admit lack of information when the context is insufficient. The GPT Model Engine receives the constructed prompt and queries GPT-3.5-Turbo via the OpenAI API. The response temperature is set to a low value (for instance, 0.2–0.3) to favour factual consistency over creativity. The answer generated is returned to the frontend, where it is rendered in the chatbot interface. For each interaction, we log the query, retrieved context IDs and model response for later analysis and potential fine-tuning.

User Model Engine

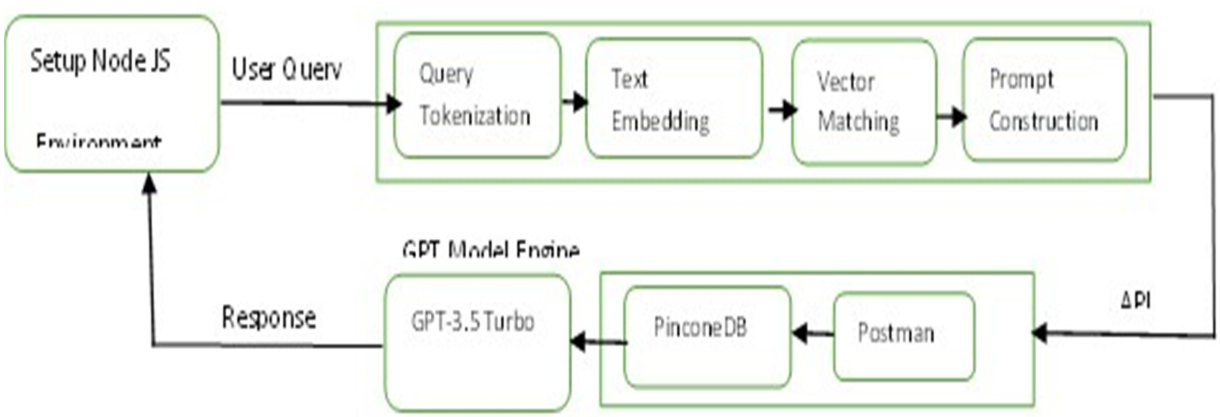

Figure 1: Proposed Registration BOT Architecture

- Model Selection

The study employed OpenAI's GPT-3.5-Turbo model as the backbone for LLM. Although more recent models (for example, GPT-4) offer higher raw performance, GPT-3.5-Turbo provides a practical trade-off between response quality, latency, and cost for a real-time university deployment.

In preliminary trials on our AAUA registration prompts, GPT-3.5-Turbo produced grammatically correct and contextually appropriate responses while keeping average response times within acceptable interactive bounds (on the order of a few seconds per query on a standard cloud deployment). The model is accessed through the official OpenAI API using stateless chat-completion interface.

- Experimental setup

To represent registration-related documents an example question–answer pairs, 'the text-embedding-ada-002` model from OpenAI, which outputs 1536-dimensional vectors for each input text segment was used. All collected knowledge items (instructions from ICT, portal usage guidelines, common registration scenarios and curated few-shot examples) are segmented into semantically coherent chunks (typically 1–3 paragraphs or a single questions and answers pair), then embedded and stored in a Pinecone vector database. We configure Pinecone with cosine similarity as the distance metric and use an approximate nearest neighbour (ANN) index (HNSW-based) to support efficient retrieval. Each record in Pinecone stores: (i) the 1536-dimensional embedding, (ii) the raw text chunk, and (iii) metadata such as source type (policy, frequently asked question, example dialogue) and timestamp. This setup allows us to retrieve the top-k most relevant chunks for a given student query in sub-second time on typical hardware, keeping total end-to-end latency dominated by the GPT-3.5 response generation.

The few-shot dataset consists of 30 question–answer (Q&A) pairs covering the most frequent registration issues at AAUA such as password reset, course correction, incomplete result display, fee payment anomalies and department transfer. 1022 samples were gathered from students for our model and for the current AAUA model, These examples were obtained through a semi-structured interview with a senior system analyst at the ICT unit and reviewing historical registration support logs. Each raw example was cleaned to remove personally identifiable information and to standardize terminology (for instance, "Avers", "school café", "ICTAC").

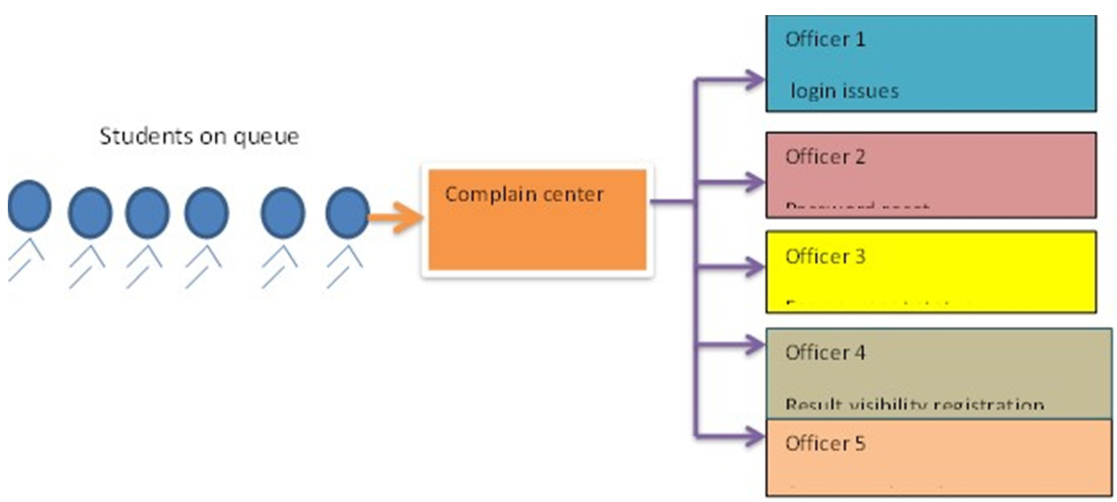

Figure 2: Students On Queue Being Attended To By ICTAC Staff

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Thereafter, tokenized and segmented the examples for each Q&A pair to form a single training item in the prompt library. For retrieval purposes, each answer and its corresponding question are embedded and stored in Pinecone as separate but linked records (via metadata), allowing the system to retrieve either canonical Q&A pairs or policy-style descriptions depending on the query. The experimental setup of our model uses one thousand five undergraduate students from different departments. Each participant interacted with the chatbot through the registration bot interface. The parameters used were login issues, password reset, fee payment status, result visibility and course registration errors as shown in Figure 2. The waiting time were recorded by our model. A similar setup is done with the current application where students queue for the same operations for complaints every 12:30pm as depicted in Figure 2. A waiting cost of #5.00 per minute is charged for student(s) who spent more than 4minutes. The cost model is depicted in Table 1.

- WAITNG COST MODEL

Table 1: Pseudocode of waiting costs

$let\ x = ave\ charge\ per\ min$
Let f = waiting time
$let\ y = waiting\ time \leq 4$
$for\ i = 1\ to\ n(No\ of\ table)$
$for\ j = 1\ to\ k(No\ of\ metrics)$
    If f >y then
        $A(i, j) = f * x$
    else
        $A(i, j) = 0$
    Endif
Next j
Next *i*

4 . RESULTS AND DISCUSSION

The measurement of our waiting time and the conventional AAUA model are shown in Table 2 and 3 respectively. Under our Chatbot Registration Model, we recorded 5, 4, 7, 5 and 7 minutes waiting on login issues, password reset, fee payment status, result visibility and course registration errors, However, in the Conventional AAUA model, 40, 14.20, 15 and 26 were recorded for the same metric. The comparative analysis of the two models based on waiting time and waiting costs are depicted in Figure 3 and 4 respectively. In Figure 3, the result shows that the Chatbot registration model recorded less waiting time in all the performance metrics used. For example, under login issues, we recorded 5minutes which outperformed 40minutes recorded under The AAUA model. On the issue of waiting costs, the Chatbot performed better than the current AAUA model. For example, under the password reset, we recorded no waiting cost as against the #150.00 recorded by AAUA.

Table 2: Proposed Chatbot Registration Model

Parameter	Online Average waiting Time (Minute)
login issues	5
password reset	4
fee payment status	7
result visibility	5
course registration errors.	7

Table 3: Conventional AAUA Model

Parameter	Arrival Time	Departure Time	Average waiting Time (Minute)
login issues	12:30 pm	1:10 am	40
password reset	12:30 pm	1.04am	34
fee payment status	12:30 pm	12.45	15
result visibility	12:30 pm	12:50am	20
course registration errors.	12:30 pm	12:56am	26

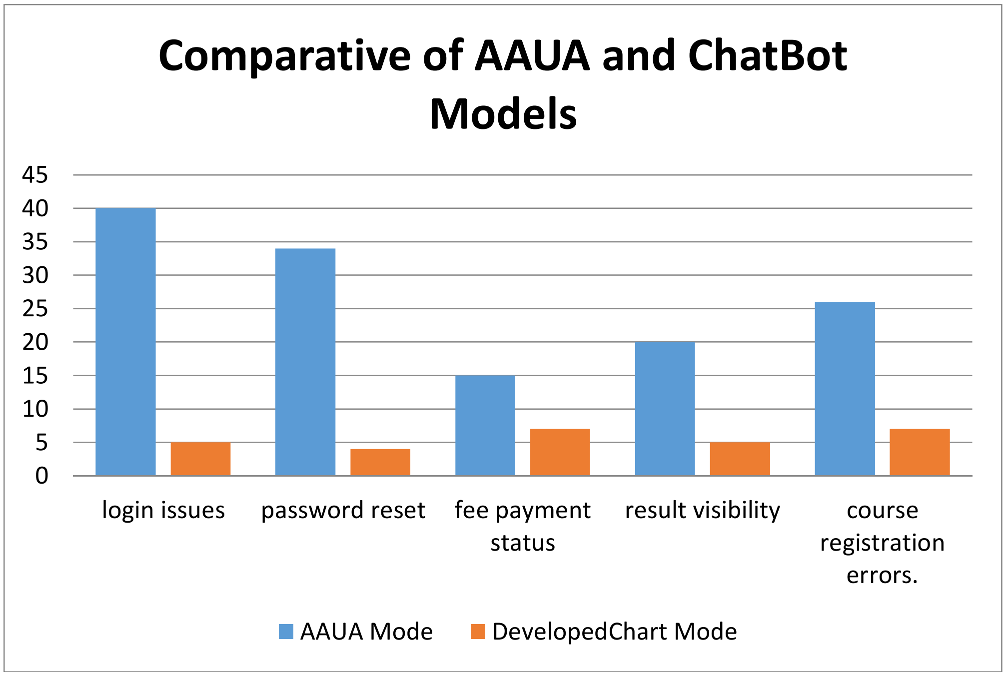

Figure 3: Comparative of AAUA and the Developed Chatbot Model

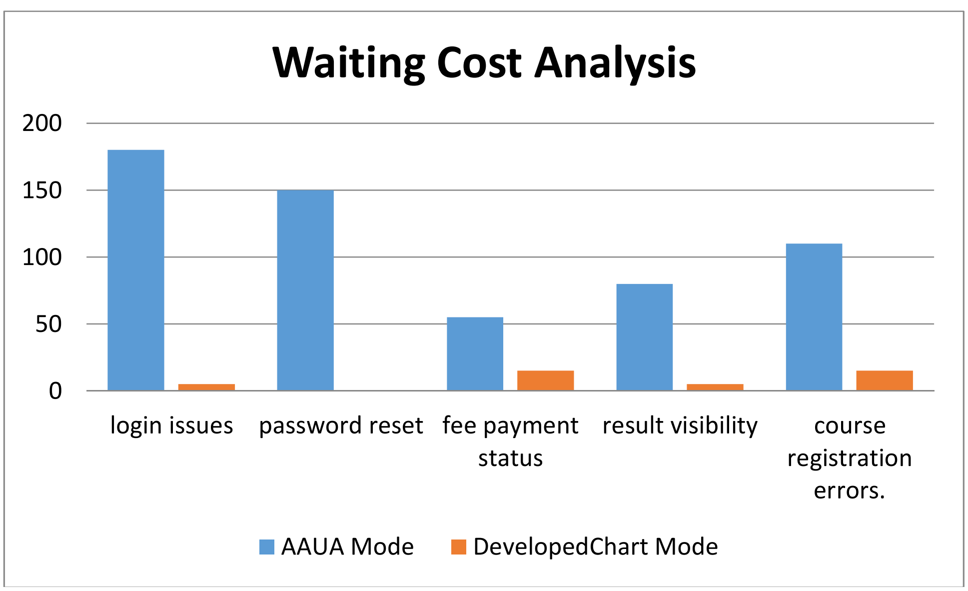

Figure 4: Waiting Cost analysis of AAUA and our Chatbot models

5. CONCLUSION AND RECOMMENDATIONS

The issue of students' registration process in higher institution of learning has been a great challenge especially in AAUA. In fact, many students collapsed in the queue while making corrections during registration in AAUA ICTAC. Many institutions and scholars have proposed and adopted various techniques. However, literature reveals that the issue of long waiting time and the cost on these students are still challenges. This paper addresses these issues by developing an automated student registration chatbot. This is done by adopting the large language model (LLM) and prompt engineering technique, the bot simplifies the registration processes and eliminates over-reliance and direct dependent on administrative support.

The waiting time and waiting cost of five major parameters were used as our performance metrics. These are login issues, password reset, fee payment status, result visibility and course registration errors. A comparative analysis is done with the existing model. Experimental results reveal waiting time of 40,14.20,15 and 26 minutes under the AAUA model and 5,4,7,5 and 7 minutes under the developed chatbot model. On the issue of waiting costs, the Chatbot performed better than the current AAUA model. For example, under the password reset, we recorded no waiting cost as against the #150.00 recorded by AAUA. The results demonstrate that the bot's waiting time and costs have a better performance over the existing model on all the metrics, thereby leading to improved administrative efficiency and better student experience. We hope to extend this work by proposing artificial intelligent to address the issues.

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